Four Aspects of Technological Change

Dissertation
submitted to the Faculty of Economics,
Business Administration and Information Technology
of the University of Zurich

to obtain the degree of
Doctor of Philosophy
in Economics

presented by

Franziska Josefine Weiss
Germany

approved in April 2014 at the request of

Prof. Dr. Fabrizio Zilibotti
Prof. Dr. George-Marios Angeletos

The Faculty of Economics, Business Administration and Information Technology of the University of Zurich hereby authorizes the printing of this dissertation, without indicating an opinion of the views expressed in the work.

Zurich, April 02, 2014

Chairman of the Doctoral Board: Prof. Dr. Josef Zweimüller

Acknowledgements

In autumn 2009 I came to join the Department of Economics at the University of Zurich. While I was working on my dissertation, I was employed as a research assistant by Prof. Dr. Fabrizio Zilibotti at the Chair of Macroeconomics and Political Economy. It was there that I learnt how to conduct rigorous research and to work independently and in a creative manner. Thus, I want to thank all current and former members of the Chair for their helpful comments and suggestions that fostered the development of my thesis. I am proud of having obtained my PhD from the University of Zurich that provides a very rich and unique research and work environment.

In particular, I am deeply indebted to my supervisor Prof. Dr. Fabrizio Zilibotti for his guidance, his motivation, his trust and his endless support. Not only academically, but also personally I have benefited from his supervision and his advice. Furthermore, I am extremely grateful to my (other) Co-authors Andreas Beerli, Timo Boppart, Michelle Rendall and Prof. Dr. Josef Zweimüller for innumerable illuminating discussions and debates that fostered our projects and had positive externalities on my own work. In addition, I feel very much obliged to Prof. Dr. George-Marios Angeletos who had a significant impact on me during the end of my dissertation and who agreed to be my Co-advisor. Finally, I wish to thank Simon Alder, Bea Kraus, Andreas Müller and Sabrina Studer for inspiring and distracting coffee breaks and for being the best office mates I could hope for. They all contributed to making my time at the University of Zurich an unforgettable era of my life.

Last but not least, I would like to thank my family, friends, my god-mother and first and foremost my parents for their great support. Especially, I owe many ideas to fruitful discussions with my father and my mom was my greatest mental mentor during all these years. They never gave up believing in me and my work and made me go on also in difficult periods. Moreover, I am thankful to Timo for his encouragement and his mere presence that enriched my life in Zurich.

Franziska Josefine Weiss, Zurich, January 2014

Contents

Part I

Dissertation Overview

Dissertation Overview

The general topic of this dissertation is technological change. This cumulative dissertation consists of four papers, that study four different aspects of technological change through an macroeconomic perspective. The New Palgrave Dictionary of Economics lays out that technological change is rarely neutral, but usually biased towards increasing the relative productivity of one specific factor of production. Hence, technological change will always produce winners and losers within society in relative terms. However, on the aggregate there is little doubt that society as a whole has been benefiting from technological progress tremendously. In fact, I believe our well-being to be closely intertwined with technological change and hence decided to focus on this issue during my time as a doctoral student at the University of Zurich.
The four essays (within this dissertation) focus on the determinants of technological change and the consequences of it on economic welfare, the labor market and the environment. The first essay looks at structural change and the resulting determinants of differential technological progress across disaggregated industries within the economy. Both theoretically and empirically it assesses the direction of technical change and its feedback on consumption behavior of agents. The second essay looks at labor market implications that result from technological change. As outlaid above, each change is likely to benefit some (types of labor) while making others worse off. The third essay relates the process of technological progress to the increasing challenge for our environment to cope with an ever rising demand for natural resources. Here it especially focuses on the role of emerging markets such as China. Finally, the last essay is directly related to the first study. Building on the theoretical implications of the first essay, it evaluates quantitatively to what extent the rising middle class in China influences innovation behavior of Chinese firms.
The remainder of this overview chapter provides a short summary of each of the four essays.

The first paper *Non-Homothetic Preferences and Industry Directed Technical Change* (joint with Timo Boppart), combines the theory of directed technical change with non-homothetic preferences in order to reconcile changes in relative expenditures of different sectors with non-constancy in relative prices and the long-run trends in relative TFP growth rates across sectors. The theoretical contribution of this paper is to provide a model of directed technical change in which structural change happens due to both relative price and income effects. In contrast to the standard theory of directed technical change, structural change is not only a transitional dynamic but a long-run process, being present even asymptotically. In contrast to the existing literature that treated the two possibly counteracting channels (which link expenditures to relative prices) separately, our approach allows for both a substitution effect and a market size effect. The substitution effect makes consumers' expenditures a function of relative prices, while the market size effect affects the growth rate of relative prices through differential spending on industries. Thus, there exists an endogenous interdependency between relative prices and the expenditure structure. Combining this with a non-homothetic preference structure allows us then to reconcile the evolution of industry prices and expenditure shares for the US economy. Although the model replicates the rich, disaggregate production structure, it still features balanced growth on the aggregate in line with Kaldor's (1961) stylized facts and can be solved by paper and pencil. In the empirical section of the paper, we use the model to evaluate the market size effect quantitatively. Using the input-output tables of the US, our theory helps us to reconstruct how structural change in terms of final consumption affects the market size of industry value-added. Arguing that the structural change across broad categories of final consumption is exogenous from the perspective of an individual firm, this gives an instrument for the industrial market size (at the value-added level). Testing for the market size effect of induced innovation our findings suggest that a 1 percent increase in an industry's market size (relative to GDP) leads to an increase in the TFP growth rate of about 0.3 percentage points over five years or equivalently to a decrease in the growth rate of relative prices of 0.6 percentage points.

My second project *Employment Polarization and the Role of the Apprenticeship System*, (joint with Michelle Rendall) analyzes in what way a specific education system fosters the investment in specific human capital at the middle skill level (apprenticeship vs. general schooling) and in turn incentives firms to adopt new (and potentially task-replacing) technologies. Recent literature has documented that machines and (ICT) technology, which are complementary to high skill workers, are increasingly replacing middle skill labor in the US, which then in turn leads to labor market polarization. Comparing this development to Germany this trend is much less pronounced, although, there exists large variation within the country itself. Using regional variation in apprenticeship training intensity (within Germany), we offer a theory that reconciles the differential regional developments in labor polarization trends. The key element is the (dual) apprenticeship system which provides incentives for firms to invest in industry- (or firm) specific human capital of its workforce. As a consequence, the middle skill group, composed primarily of skilled apprentices, has acquired a highly specific skill at the expense of firms/governments (in contrast to middle skilled that received general education like in the US). Apprentices tend to be more productive than those without industry-specific training when operating machinery and processes learned during the training years. However, from the firms perceptive, acquiring new machinery is more costly, since the old training (specific skills) becomes obsolete and the comparative advantage acquired through specific training during the apprenticeship is lost. Moreover, if ICT capital replaces middle skilled workers, firms in apprentice-intensive regions have a smaller incentive to adopt new technologies. Based on our theory we make use of a large German dataset with detailed regional variation and evaluate the effect of falling capital prices on technology adoption and the resulting polarization the labor market. Finally, the model also offers an explanation for the faster structural transformation of the US (in terms of service sector growth) due to higher labor mobility and labor replacement (by capital) in manufacturing.

The third paper *Directed Technical Change, The Environment and the Role of Emerging Markets* studies the consequences of lacking environmental standards in emerging economies and its interaction with the form of technological progress (imitation vs. innovation). In particular, this study asks three questions: First, are the policies imposed in industrialized economies sufficient to prevent a global environmental disaster? Second, what happens when firms in emerging economies become innovators instead of mere imitators? Third, what are the economic consequences for countries subject to tighter environmental regulations? ls there a risk of a race to the bottom? The paper tries to answer these questions in a directed technical change model, where entrepreneurs invest either in "dirty" or "clean" production techniques. By extending the model into a global perspective and introducing a negative pollution externality, I analyze the interaction between unilateral environmental regulations and the direction of R&D investments that are shaped endogenously. Specifically, assuming the enforcement of environmental policies in the North (i.e. the industrialized countries), I focus on the condition that makes it profitable for entrepreneurs in emerging markets to invest in sustainable technologies. I find that whenever the unregulated country is close to the technological frontier and effective in innovation tasks, unilateral policies (only enforced in the industrialized countries) fail to prevent an environmental disaster. In addition, only through the enforcement of environmental regulations, the North loses its role as the technological leader. In contrast, whenever the unregulated country is unable to leapfrog ahead, unilateral regulations within the technologically leading country ensure a sustainable growth path. Finally, I present empirical evidence (on R&D expenditure and patents) suggesting that China is indeed very close to the technological frontier. Hence, the paper calls for a stricter international coordination to enforce regulations at the global rather than at the regional level.

What is the effect of the rapidly growing middle class in China on innovation activities of Chinese manufacturing firms? Why do sectors differ to such a large extent in their development? Motivated by these questions, the fourth project *Demand Forces of Technical Change, Evidence from the Chinese Manufacturing Industry* (together with Andreas Beerli, Fabrizio Zilibotti and Josef Zweimüller) analyzes the interplay between the rapidly growing middle class of new consumers and the process of technical change in the Chinese economy. Merging the insights of the two recent theories of "directed technical change" and "non-homothetic preferences", yields the prediction that economic growth brings about demand-driven waves of technical progress. Thus, this paper investigates the effect of market size on innovation activities across different durable good industries in the Chinese manufacturing sector. In particular, we construct a measure of potential market size that is driven only by changes in the Chinese aggregate income distribution and exogenous to changes in prices and qualities of durable goods. Results indicate that an increase in market size by one percent leads to an increase of 0.27% in firm-specific total factor productivity and an increase in labor productivity by 0.42%.

Part II of this dissertation contains the four research papers, while all Appendices are relegated to Part III. The bibliography is found in Part IV of this book. Finally, Part V contains the curriculum vitae.

Part II

Research Papers

1 Non-homothetic Preferences and Industry Directed Technical Change

Joint with Timo Boppart

1.1 Introduction

Structural change – defined as changes in relative expenditures of different sectors – is according to Kuznets (1973) one of the six main features of modern economic growth and development. In addition, differences in productivity growth rates across sectors generate systematic relative price dynamics. The literature provides two theoretically robust mechanism which link the sector-specific expenditure structure to relative prices: on the one hand, if sectors differ in their total factor productivity (TFP) growth rates, relative prices change over time and structural change can be the result. This mechanism was emphasized by Baumol (1967), who illustrates that the nominal expenditure structure is affected by relative price changes whenever the elasticity of substitution is unequal to unity. Ngai and Pissarides (2007) implement this channel in a neoclassical growth model with intertemporal optimization and balanced growth on the aggregate.

On the other hand, the literature on directed technical change emphasizes that changes in the relative market size of different sectors translate into changes in sector-specific R&D investments, which in turn determine the relative TFP growth rate and finally the dynamics of the relative price. This second mechanism goes back to Schmookler (1962) and Griliches and Schmookler (1963) and was first formalized in a dynamic general equilibrium setting in Acemoglu (1998), Acemoglu and Zilibotti (2001) and Acemoglu (2002). If expenditure shares change over time, a theory of induced innovation suggests that an increasing fraction of total R&D activity concentrates on sectors with an increasing expenditure share. This intensified R&D activity translates into an increase in the relative TFP growth rate and consequently into a decrease in the relative price growth of sectors with a rising output share.

Interestingly, in these two theoretical approaches above, the causality of the link between expenditure shares and relative price dynamics runs in different directions. This makes empirical identification difficult and has contributed to the fact that empirical quantification of the two channels remains relatively rare.[1] As an additional (theoretical) challenge, relative price changes are not the only driver of structural change. Whenever preferences are non-homothetic, income effects also determine the demand structure, along any growth path with increasing living standards. However, although there is ample evidence that this channel is quantitatively important, we are not aware of any theory of directed technical change which does allow for non-homothetic preferences.[2]

The theoretical contribution of this paper is to provide a model of directed technical change in which structural change happens due to both relative price and income effects. In contrast to the standard theory of directed technical change, structural change will not only be a transitional dynamic but a long-run process, being present even asymptotically. Within the model, there are two final consumption goods which enter the instantaneous utility function of households. Both final goods are produced using an identical set of intermediate industries, varying only in the intensities with which these are used. Due to these intensity differences, structural change in terms of final output goods trickles down to a structural change in terms of industry value-added. Since the endogenous innovation process takes place at the industry level, changes in industrial market sizes induce a shift in industry-specific R&D investments, which finally determines the evolution of final output prices. Although the model replicates this rich, disaggregate production structure, it still features balanced growth on the aggregate in line with Kaldor's (1961) stylized facts and can be solved by paper and pencil.

In the empirical section, we use US industry level data to test the "market size hypothesis" explicitly. In line with our theory, our strategy is to construct an industry-specific exogenous variation in market size that allows to separate the market size effect from the (potentially counter-acting) substitution effect. More specifically, we instrument the *industrial* market size by structural change at the *final output level*. We use the input-output relationship of the US economy (similar to Herrendorf, Rogerson and Valentinyi, 2009) in order to determine how shifts on the final output level affect the industrial value-added structure. The identifying assumption of this IV approach is that an individual firm – which makes its R&D investment decision – takes variations in the potential industrial market size, caused by aggregate demand shifts, as exogenously given.[3] Our results suggest that there is indeed a positive market size effect and TFP growth tends to increase in industries which inherently gain from the structural change on the level of final

[1] Acemoglu and Linn (2004) is a notable exception showing evidence for a causal link between market size and innovation within the US pharmaceutical industry.

[2] Allowing for non-homotheticity of preference is for instance an important difference to the paper by Ngai and Samaniego (2011).

[3] Note that in contrast to Acemoglu and Linn (2004), our strategy enables us to evaluate the market size hypothesis across the complete set of US industries.

consumption goods.
The rest of the paper is organized as follows: the next section gives a motivating example of structural change and directed technical change, before Section 1.3 proceeds with the theoretical model. Our empirical test for the market size effect is provided in Section 1.4. Finally, Section 1.5 concludes.

1.2 Motivating Example

We motivate this paper's main mechanism with US data of the durable and non-durable good sector. Figure 1.1 plots the total nominal expenditures on non-durable goods relative to total expenditures on durables on a logarithmic scale. Apart from the volatility due to recessions and World War II, the series has a strong negative trend (see dashed line). The annual growth rate of non-durable goods expenditures is on average 1.32 percentage points lower than the one of durable goods.
The corresponding price of non-durable relative to durable consumption goods is plotted in Figure 1.2. On a logarithmic scale, this series is clearly nonlinear, highlighting that the growth rate of the relative price is systematically changing over time.[4] The growth rate of the relative price of non-durables (i.e., the slope of the series in Figure 1.2) increases continuously, being slightly negative in the thirties and clearly positive around 2012. A quadratic fit to the relative price series (see dashed line) suggests that the annualized growth rate of the relative price increases each year by about 0.048 percentage points. While it was *minus* 0.74 percent in 1930, it is *plus* 3.18 percent in 2012. As long-run dynamics in relative sectoral prices are typically explained by differences in sector-specific total factor productivity (TFP) growth rates, the convex relative price path (on a logarithmic scale) depicted in Figure 1.2 indicates a huge shift in the *direction* of technical progress. This view is confirmed by Figure 1.3 which displays the decreasing time trend of the relative TFP growth rate of the non-durable compared to the durable sector. Consequently, explaining the relative price path depicted in Figure 1.2 requires a theory of sector-specific endogenous growth.
Combining Figures 1.1 and 1.2 demonstrates that a theory of structural change that relies solely on substitution effects is insufficient to explain the data. First, the fact that nominal expenditures of the durable sector – whose relative price decreases – expand faster requires the elasticity of substitution to be larger than unity. In the structural change literature this case is regarded as empirically less relevant. Second, although the relative

[4]The patterns outlined in Figure 1.1 and 1.2 are not an artifact of focusing on nominal personal consumption expenditures. The facts are unchanged when plotting total output of the durable and non-durable sector (see Figure A.1 in Appendix A.4). In addition, Figure A.2 in Appendix A.4 shows that the non-durable good sector is also expanding in real terms at a slower rate than the durable good sector.

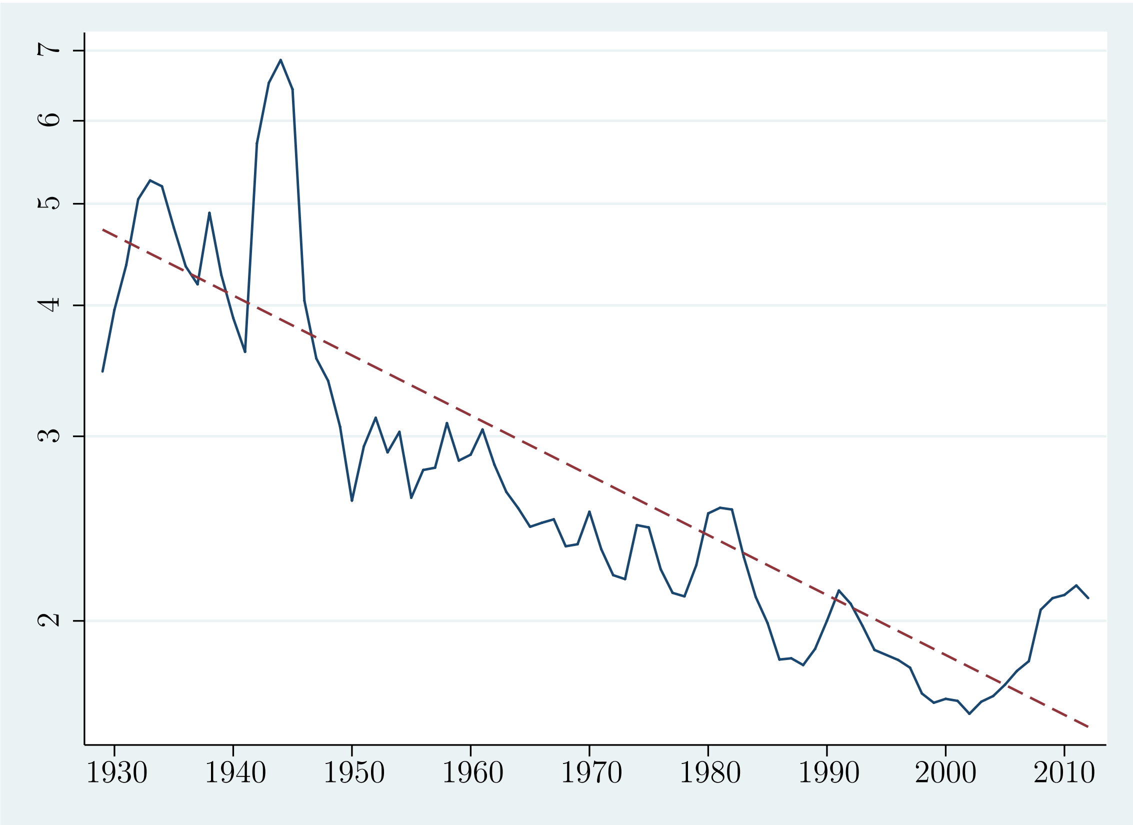


Figure 1.1: **Nominal personal consumption expenditures on non-durables relative to expenditures on durables**

Notes: The figure plots the nominal personal consumption expenditures devoted to non-durable goods relative to the one devoted to durable goods in the US for 1929-2012 on a logarithmic scale. If we regress the logarithm of the relative expenditures on a constant and the year, the slope coefficient is -0.01316 with a standard error of 0.00078.
Source: BEA, NIPA table 2.4.5.

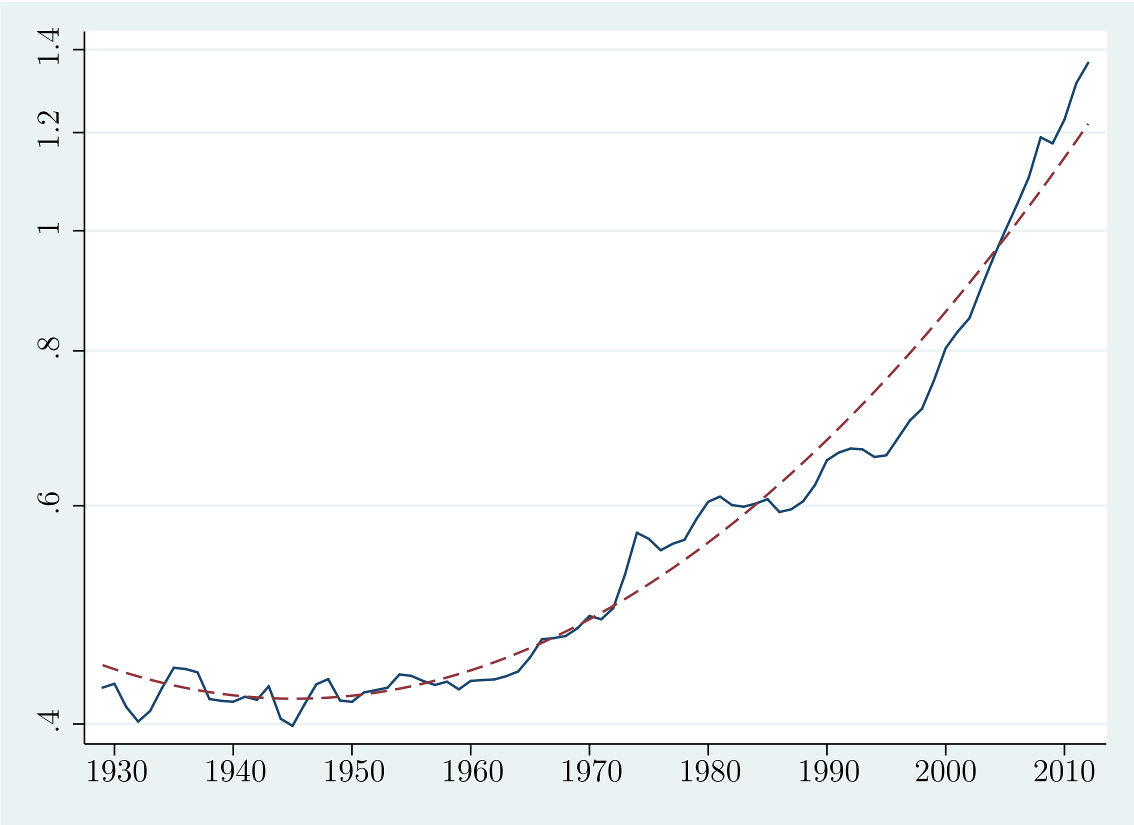


Figure 1.2: **Relative consumer price index of non-durables relative to durables**

Notes: The figure plots the relative price between non-durables and durables in the US for 1929-2012 on a logarithmic scale. If we regress the logarithm of the relative price on a constant and the year in level and squared, the slope coefficients are -0.92990 and 0.00024 respectively (with standard errors of 0.04609 and 0.00001). The relative price is normalized to one in the year 2005.
Source: BEA, NIPA table 2.4.4.

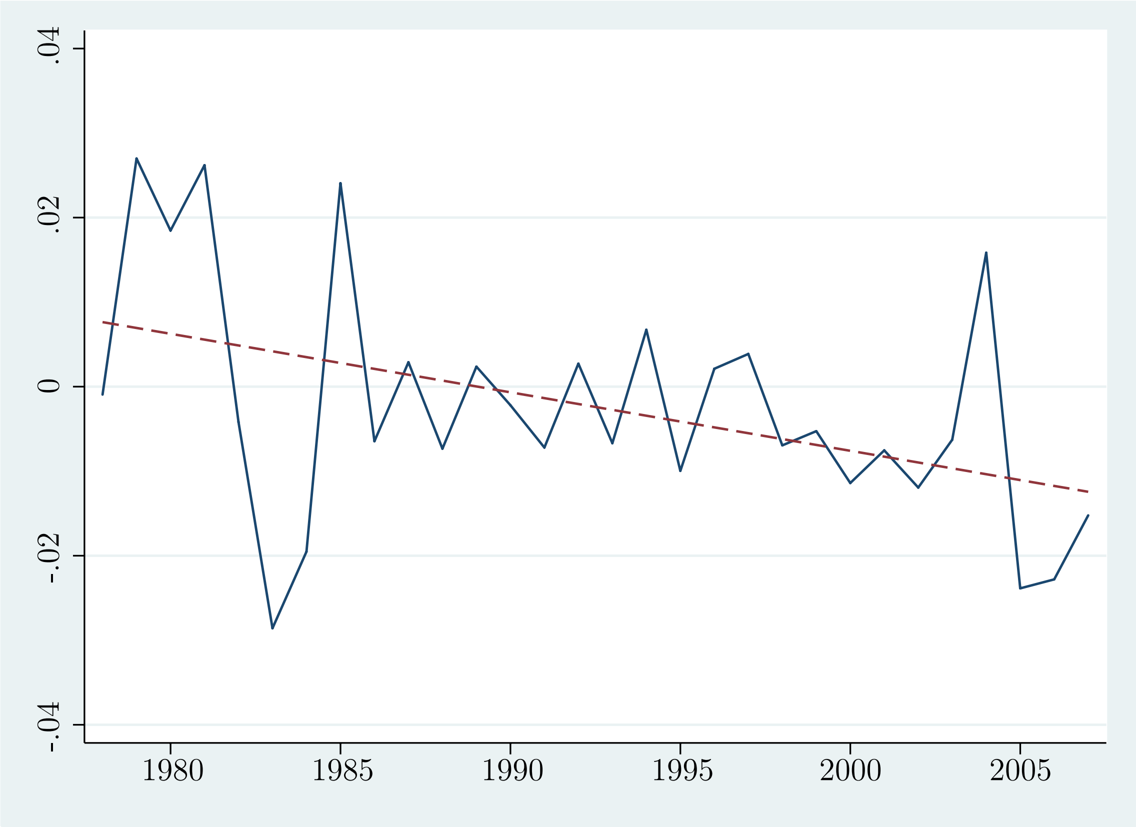


Figure 1.3: **Difference between TFP growth rates of non-durables and durables**

Notes: The figure plots the difference between the rate of TFP growth of non-durables and the TFP growth rate of durables for the years 1978-2007 using input coefficients from I-O tables as weights. The slope of the fitted line is given by -0.00069 with a standard error of 0.00027. The information of input-output tables is used to calculate the value-added industry weights of final non-durable/durable consumption. Then, the calculated TFP growth rate in terms of final consumption is the weighted average of the industries' value-added TFP growth (where the weights are these input-output coefficients). For more details see Appendix A.3. Source: EU KLEMS; BEA, NIPA table 2.4.5, own calculation.

price barely changed over the first thirty years of the observed period, structural change is present even then. These two facts require a theory which allows for non-homothetic preferences and thus includes income effects as an additional driver of structural change.[5] Moreover, the sweeping change in the expenditure structure (see Figure 1.1), which persists for more than eight decades, calls for a theory in which structural change is a long-run phenomenon.

Motivated by this illustrative example, we proceed to present our theoretical model.

1.3 Theoretical Model

1.3.1 Terminology of "Sectors" and "Industries"

We develop a theory of directed technical change, where structural change is driven by both an income and a relative price effect. Preferences are specified over two final consumption goods. A luxury good with an expenditure elasticity of demand larger than unity, called the "durable" and a necessary good with an expenditure elasticity of demand strictly smaller than unity, called "non-durable". The durable and non-durable goods are the two *sectors*. Both final goods are produced using the *same* set of intermediate inputs, which consists of different *industries* $i \in [0, 1]$. And the production processes of the two final consumption goods differ in their intensities with which they rely on a specific industry i.

1.3.2 Production

Production of the Final Good in the Two Sectors

Both durable and non-durable goods are produced competitively with Cobb-Douglas technologies defined over the same unit interval of intermediate inputs, $\{x_i(t)\}_{i=0}^1$,

$$Y_D(t) = \exp\left[\int_0^1 \log\left[x_i(t)\right] di\right]$$

[5]Especially, in the context of durable and non-durable goods the importance of income effects are incontestable as food expenditures account for 48.1 percent of non-durable expenditures in the year 1929 and Engel's law is regarded as one of the most robust empirical findings in economics (see Engel 1857, Houthakker, 1957 and Browning, 2008). This view is confirmed by Figure A.4 in Appendix A.4, which plots the fraction of goods expenditures devoted to durables for each income quartile of the US on a logarithmic scale. Richer household devote a systematically larger fraction of their goods expenditures to durable goods.

and

$$Y_N(t) = \exp\left[\Delta t\right] \exp\left[\int_0^1 \alpha(i) \log\left[x_i(t)\right] di\right] B.$$

The term $\Delta \gtreqless 0$ captures (potential) exogenous differences in the relative sector-specific productivity growth rate and B is a normalizing constant

$$B = \exp\left[-\int_0^1 \alpha(i) \log\left[\alpha(i)\right] di\right].$$

Production of both final goods relies on the same set of intermediate inputs. However, the two sectors use them with different intensities. While the output elasticity of intermediate input $x_i(t)$ is unity in the durable good sector, it is $\alpha(i) \geq 0$ in the non-durable sector. We have $\int_0^1 \alpha(i)di = 1$ and we denote the variance of the $\alpha(i)$'s by $\sigma^2 \geq 0$, i.e. $\sigma^2 \equiv \int_0^1 \alpha(i)^2 di - 1$. If $\sigma^2 = 0$, the weights of the intermediate inputs are exactly the same for both final good sectors. In contrast, the larger σ^2, the more intensities differ across the two sectors.

Since final output markets are competitive the prices will be equal to the marginal cost. We set the durable good as the numeraire, i.e., we have

$$1 = \exp\left[\int_0^1 \log\left[p_i(t)\right] di\right], \tag{1.1}$$

and the (relative) price of the non-durable good is given by

$$P_N(t) = \exp\left[-\Delta t + \int_0^1 (\alpha(i) - 1) \log\left[p_i(t)\right] di\right], \tag{1.2}$$

where $p_i(t)$ is the price of intermediate industry input i.[6] The relative price between non-durable and durable goods, $P_N(t)$, changes for two reason. First, if $\Delta \neq 0$, there is an exogenous difference in the productivity growth rates which leads to a trend in relative prices. Second , as long as the two sectors use industries $i \in [0, 1]$ with different intensities, i.e., $\sigma^2 \neq 0$, dynamics in intermediate industry prices $p_i(t)$ also affect $P_N(t)$.

In the following we explain industry-specific price changes by endogenous technical progress at the intermediate industry level.

[6]The righthand sides of (1.1) and (1.2) represent the unit cost of the corresponding production functions in terms of the numeraire.

Production of Intermediate Inputs

The intermediate inputs are produced competitively according to a standard "lab-equipment model" (see e.g. Acemoglu, 2009),

$$y_i(t) = \frac{\nu}{\nu - 1} \left[\int_0^{M_i(t)} \chi(\omega_i, t)^{\frac{\nu-1}{\nu}} d\omega_i \right] L_i(t)^{\frac{1}{\nu}}, \tag{1.3}$$

where $\nu > 1$. $L_i(t)$ denotes labor used in intermediate input production of industry i. Labor is fully mobile across sectors and earns a wage rate $w(t)$. $\chi(\omega_i, t)$ is the amount of "machines" of variety ω_i that is used in the production of intermediate i. At a given date t, $M_i(t)$ denotes the number of different available machine varieties. The marginal costs of a machine $\chi(\omega_i, t)$ are $\psi_i(t) = \frac{\nu-1}{\nu} p_i(t)$, i.e. $\frac{\nu-1}{\nu}$ units of intermediate input $y_i(t)$. Each machine producer acts as a monopolist. Under these assumptions, firms' optimization implies the results that are summarized in the following lemma.

Lemma 1.1. *Each machine producer sets its price at each point in time equal to*

$$p(\omega_i, t) = \frac{\nu}{\nu - 1} \psi_i(t) = p_i(t), \ \forall \omega_i. \tag{1.4}$$

Cost minimization and perfect competition at the intermediate industry level implies

$$\chi(\omega_i, t) = L_i(t), \ \forall \omega_i, \tag{1.5}$$

and

$$p_i(t) = (\nu - 1) \frac{w(t)}{M_i(t)}, \ \forall i, \tag{1.6}$$

where w is the wage rate. Then, at a given point in time, each monopolist ω_i earns a profit flow of

$$\pi(\omega_i, t) = \frac{\nu - 1}{\nu} \frac{w(t) L_i(t)}{M_i(t)}, \ \forall \omega_i. \tag{1.7}$$

The total amount of produced intermediate inputs i can be expressed as

$$y_i(t) = \frac{\nu}{\nu - 1} M_i(t) L_i(t). \tag{1.8}$$

The total amount of intermediate inputs i used to produce machines ω_i is

$$c_i(t) = \frac{\nu - 1}{\nu} M_i(t) L_i(t). \tag{1.9}$$

Proof. See Appendix A.1. □

So far the number of available machine varieties, $M_i(t)$, has been treated as exogenous.

As a next step we specify how a new machine variety can be introduced.

Production Possibilities Frontier

By spending $\frac{1}{\eta}$ units of output of industry i as R&D investments, a new machine variety $\chi(\omega_i, t)$ can be invented. Hence, we have

$$\dot{M}_i(t) = \eta z_i(t), \tag{1.10}$$

where $z_i(t)$ denotes intermediate inputs of type i used for R&D investments (in industry i). There is free entry into research and a successful innovator obtains a perpetual patent on a machine variety ω_i. $M_i(0)$, $\forall i$ is exogenously given and we assume $M_i(0) = 1$, $\forall i$.[7] Considering a situation with positive R&D investments in all industries i, we obtain the following Lemma.

Lemma 1.2. *With positive R&D investments, the value of a machine producing firm is given by*

$$v(\omega_i, t) = v_i(t) = \frac{w(t)(\nu - 1)}{\eta M_i(t)}, \ \forall \omega_i. \tag{1.11}$$

Moreover, we must have

$$r(t) - \frac{\dot{w}(t)}{w(t)} + \frac{\dot{M}_i(t)}{M_i(t)} = \frac{\eta L_i(t)}{\nu}, \ \forall i. \tag{1.12}$$

Proof. See Appendix A.1. □

In order to close the model we need to specify the demand side of the economy. As motivated in Section 1.2 this demand side has to allow for non-homothetic preferences.

1.3.3 Demand Side

Suppose we have a unit interval of identical households endowed with L units of inelastically supplied labor and $A(0)$ units of (initial) wealth. Each household has the following preferences

$$\mathcal{U}(0) = \int_0^\infty \exp(-\rho t) \left[\frac{1}{\epsilon} E(t)^\epsilon - \frac{\beta}{\gamma} P_N(t)^\gamma - \frac{1}{\epsilon} + \frac{\beta}{\gamma} \right] dt, \tag{1.13}$$

where $\rho > 0$ is the rate of time preferences and the term in squared brackets is the indirect instantaneous utility function. This instantaneous utility function is defined over the nominal expenditure level, $E(t)$, and the prices of durables and non-durables. But

[7] This assumption is not crucial, but simplifies the analysis. Basically, as we will see below, it normalizes all relative prices between any two intermediate inputs to one at $t = 0$.

as we have chosen the price of durables as our numeraire, only the (relative) price of non-durables, $P_N(t)$, shows up in (1.13). We have $0 < \epsilon < 1$, $\gamma \leq \epsilon$ and $\beta > 0$. The intratemporal preferences are identical to Boppart (2011) and are a subclass of "price independent generally linearity" (PIGL) preferences specified in Muellbauer (1975) and Muellbauer (1976).[8] The virtue of these preferences is that, although they are non-homothetic (and moreover do not fall into the Gorman class), the analysis of intertemporal optimization is very tractable.
The intratemporal preferences are only well defined if the expenditure level exceeds a certain threshold. In order to ensure this, we assume henceforth

$$E(t)^{\epsilon} \geq \beta P_N(t)^{\gamma}. \tag{1.14}$$

This condition will be fulfilled as long as the factor endowments L and $A(0)$ are "sufficiently large". A condition in terms of exogenous model parameters which guarantees (1.14) is stated later on. Total consumption expenditures, $E(t)$, are spent on durables, $X_D(t)$ and non-durables, $X_N(t)$. Applying Roy's identity yields the following demand system:

Lemma 1.3. *Intratemporal optimization implies*

$$X_D(t) = E(t) - \beta E(t)^{1-\epsilon} P_N(t)^{\gamma}, \tag{1.15}$$

$$X_N(t) = \beta E(t)^{1-\epsilon} P_N(t)^{\gamma-1}, \tag{1.16}$$

at each date in time.

Proof. Deriving the optimal consumption structure is just an application of Roy's identity. □

We see that the demands are non-linear functions of the expenditure level $E(t)$. Hence, we have non-homothetic preferences.[9] Condition (1.14) ensures the consumed quantities to be non-negative. The expenditure share devoted to non-durables, $S_N(t) \equiv \frac{P_N(t)X_N(t)}{E(t)}$, can be written as

$$S_N(t) = \beta E(t)^{-\epsilon} P_N(t)^{\gamma}. \tag{1.17}$$

[8] For more detail on these preferences, the reader is referred to Boppart (2011), where it is shown that these preferences remain very tractable even if we allow for household heterogeneity and population growth. However, note that the parameter space is slightly different compared to Boppart (2011) in order to allow for cases where the elasticity of substitution exceeds unity.

[9] The class of preferences (1.13) does enclose a homothetic case with $\epsilon \to 0$. But in this paper we focus on the more interesting non-homothetic cases with $\epsilon > 0$.

Clearly, $S_N(t)$ is declining in $E(t)$ and Engel's law applies.[10] The expenditure elasticity of demand and the elasticity of substitution are the two elasticities that control the effects of changes in expenditure levels and relative prices on the demand structure. The expenditure elasticity of demand for non-durables is equal to $1-\epsilon$, which is strictly smaller than unity. Moreover, the elasticity of substitution is given by $1-\gamma+(\epsilon-\gamma)\frac{S_N(t)}{1-S_N(t)}$. So the elasticity of substitution is in general time varying and can be either larger or smaller than unity, depending on the parameter γ.[11] Overall, this means that both the income and substitution channel of structural change are present in the model and their importance is controlled by the parameters ϵ and γ.

Next, we turn to the household's intertemporal optimization problem. The household takes the interest rate, $r(t)$, and wage rate, $w(t)$, as given and maximizes (1.13) subject to the flow budget constraint and the transversality condition, which read

$$\dot{A}(t) = r(t)A(t) + w(t)L - E(t) \text{ and } \lim_{t\to\infty} E(t)^{\epsilon-1}A(t)\exp\left[-\rho t\right] = 0. \tag{1.18}$$

This yields the following Lemma:

Lemma 1.4. *Intertemporal optimization implies the following Euler equation*

$$(1-\epsilon)\frac{\dot{E}(t)}{E(t)} = r(t) - \rho. \tag{1.19}$$

Proof. See Appendix A.1. □

This is the familiar form of the Euler equation which is consistent with a constant growth path along which the saving and interest rate are constant. Note that we obtain this simple Euler equation although intratemporal preferences are non-homothetic.

1.3.4 Market Clearing and Resource Constraints

Market clearing at the final output sector level implies

$$Y_j(t) = X_j(t),\ j = \{D, N\}. \tag{1.20}$$

[10] Interestingly, it is even consistent with the functional form Ernst Engel had in mind while studying the expenditure structure of Belgian workers. See Engel (1857), p. 30: "Das Gesetz, mit welchem man es hier zu thun hat, ist kein einfaches. Die Höhe der Ausgaben für Nahrung wachsen bei Abnahme des Wohlstandes in einer geometrischen Progression."

[11] As it will be shown later on, we have $\lim_{t\to\infty} S_N(t) = 0$, so $1-\gamma$ can be interpreted as the asymptotic elasticity of substitution.

On the industry level, market clearing requires

$$y_i(t) = \tilde{x}_i(t) + c_i(t) + z_i(t),\ \forall i \in [0,1]\,, \tag{1.21}$$

where $y_i(t)$ is total production of intermediate inputs. $\tilde{x}_i(t)$ is the total amount of intermediate inputs used in final goods production. $c_i(t)$ are total intermediate inputs used to produce machines and $z_i(t)$ are total intermediate inputs used as R&D investments. Labor market clearing can be written as

$$L = \int_0^1 L_i(t)di. \tag{1.22}$$

Finally, asset market clearing implies

$$A(t) = \int_0^1 M_i(t)v_i(t)di. \tag{1.23}$$

1.3.5 Dynamic Equilibrium

In this economy, a *dynamic equilibrium* is defined as follows:

Definition 1.1. *A dynamic equilibrium is a time path of expenditure, wealth and consumption quantities* $\{E(t), A(t), X_N(t), X_D(t)\}_{t=0}^{\infty}$*, prices, wage rate and interest rate* $\{P_N(t), w(t), r(t)\}_{t=0}^{\infty}$*, available machine varieties, output, labor demand, R&D investment and price in each industry* $\{M_i(t), y_i(t), L_i(t), z_i(t), p_i(t)\}_{t=0}^{\infty}$*,* $i \in [0,1]$*, and quantity and price of all machines varieties in all industries* $\{\chi(\omega_i, t), p(\omega_i, t)\}_{t=0}^{\infty}$*,* $\forall \omega_i, i \in [0,1]$ *which are jointly consistent with household and firm optimization, the resource constraint and market clearing, given the specified market structure (i.e. perfect competition in all markets with the exception of the machine producers who have a monopoly position).*

Before solving the model, we briefly relate the specified framework to some reference cases. First, with $\beta = 0$, the representative household only consumes good D (i.e. durables). In this case, the perfectly symmetric unit interval of intermediate inputs becomes obsolete and the economy coincides with the standard one-sector lab-equipment model where households have CRRA preferences (see e.g. Acemoglu, 2009, chapter 13). Second, with $\epsilon \to 0$, $\sigma^2 = 0$ and $\Delta \neq 0$, we have homothetic preferences and identical technologies across sectors – with the exception of a Hicks-neutral exogenous but sector-specific TFP growth rate. In this case, the model is very similar to Ngai and Pissarides (2007). The equilibrium dynamics feature structural change due to relative price effects and we can solve the model explicitly since the Kaldor facts will be fulfilled.[12] However, such an analysis clearly abstracts from biased technical change and there would be no income effects on the demand structure. Third, with $\epsilon \neq 0$, $\sigma^2 = 0$ and $\Delta \neq 0$, the model becomes similar to Boppart (2011) where structural change is driven by the non-homotheticity of preferences. But since $\sigma^2 = 0$ structural change at the sector level does not trickle down to intermediary inputs and hence does not induce directed technical change on the industry level. Finally, if we consider homothetic preferences (i.e. $\epsilon \to 0$), introduce two different types of labor (skilled and unskilled), and assume that different intermediate industries use these two labor types with different intensities, we move towards a standard model of directed technical change a la Acemoglu (1998).

It is important to emphasize that none of the aforementioned models contain all the characteristics motivated in Section 1.2. In the next subsection we solve our model and show that it features industry directed technical change while the long-run structural change is driven by both an income and a substitution effect.

1.3.6 Solving for the Dynamic Equilibrium Path

Aggregate Dynamics

We solve the model in two parts: first, we show that the dynamic equilibrium path features standard balanced properties on the aggregate (i.e. the Kaldor facts are fulfilled). Second, we characterize the sectoral dynamics. This is more complicated since we have to deal with relatively rich dynamics at the disaggregate level. But irrespectively of these sectoral dynamics, the next proposition shows that on the aggregate the model has a unique dynamic path with a closed form solution.

Proposition 1.1. *Suppose we have $\frac{\eta L}{\nu} > \rho > \frac{\epsilon \eta L}{\nu}$. Then, the model features no transitional dynamics and the real (durable good denominated) interest rate and the growth rates of wealth, wages and expenditures are constant, i.e.*

$$r = \frac{\eta L}{\nu} \tag{1.24}$$

$$\frac{\dot{A}(t)}{A(t)} = \frac{\dot{w}(t)}{w(t)} = \int_0^1 \frac{\dot{M}_i(t)}{M_i(t)} di = \frac{\dot{E}(t)}{E(t)} = \frac{1}{1-\epsilon}\left[\frac{\eta L}{\nu} - \rho\right] \equiv g > 0. \tag{1.25}$$

Moreover, we have

$$w(t) = \frac{1}{\nu - 1} \exp\left[gt\right], \tag{1.26}$$

[12] The reason why the model would not be identical to Ngai and Pissarides (2007) is due to the fact that they use a CES utility function, whereas in our model the elasticity of substitution between durables and non-durables is not constant over time.

and

$$E(0) = \left[\frac{L}{\nu - 1} + \frac{1}{(1-\epsilon)\eta}\left[\rho - \frac{\epsilon\eta L}{\nu}\right]\right] \equiv \mathcal{E}_0 > 0. \tag{1.27}$$

This is an equilibrium path as long as (1.14) *is fulfilled for all* t.

Proof. See Appendix A.1. □

Proposition 1.1 shows that the aggregate variables behave in the dynamic equilibrium as in the steady state of a neoclassical growth model and Kaldor's stylized facts (see Kaldor, 1961) are fulfilled. It is noteworthy that we can solve for the aggregate dynamics without knowing the exact equilibrium path of the disaggregate variables. This separation keeps the problem tractable and allows us to find a closed form characterization of the disaggregate dynamics, as we will show in the next step.

Disaggregate Dynamics

The disaggregate equilibrium dynamics of this model are much richer than the aggregate, because the expenditure structure, $S_N(t)$, and the intermediate input prices, $\{p_i(t)\}_{i=0}^{1}$, interact with each other in two ways. On the one hand, the dynamics of intermediate input prices affect the (relative) price of non-durable goods, $P_N(t)$, and consequently via a standard substitution effect the demand structure $S_N(t)$. On the other hand, as in any theory of directed technical change, the demand structure determines the (industry-specific) R&D investment incentive and via this channel the dynamics of intermediate industry prices. Interestingly, the causality of the two effects go in different directions. The two effects are highlighted in the next lemma.

Lemma 1.5. *The disaggregate dynamics can be summarized by the following equations:*

$$S_N(t) = \beta\mathcal{E}_0^{-\epsilon}\exp\left[-\epsilon g t - \gamma\Delta t + \gamma\int_0^1 [\alpha(i) - 1]\log[p_i(t)]\,di\right], \tag{1.28}$$

and

$$p_i(t) = \exp\left[-\eta\frac{\nu-1}{\nu}\mathcal{E}_0\int_0^t S_N(\tau)\,[\alpha(i)-1]\,d\tau\right], \forall i, \tag{1.29}$$

where expenditures at date zero, $\mathcal{E}_0$, *and the growth rate,* g, *are defined in Proposition 1.1.*

Proof. See Appendix A.1. □

(1.28) visualizes the substitution effect of intermediate industry prices on the demand structure, whereas (1.29) formalizes the directed technical change effect from the expenditure structure on the industry price dynamic.

The expenditure share of the non-durable sector, $S_N(t)$, changes over time for two reasons: first, households have non-homothetic preferences and (per-capita) expenditures grow along the dynamic equilibrium path with rate g. Since non-durables are necessities and durables luxuries, $S_N(t)$ tends to decline over time. The magnitude of this effect is governed by the degree of non-homotheticity of preferences, ϵ, and the growth rate of (per-capita) expenditures, g. With homothetic preferences (i.e. $\epsilon = 0$) we would have no income effect on the demand structure and the corresponding term in (1.28) would vanish. The second reason why $S_N(t)$ changes over time is that the relative price $P_N(t)$ varies. Clearly, the relative price changes due to the exogenous difference in TFP growth rates, Δ. But in addition, $P_N(t)$ varies since there are differences in the intensities with which the sectoral outputs depend on the different intermediate industries (represented by the $\alpha(i)$'s) and since industry-specific prices, $p_i(t)$, change according to directed technical progress. The sign and magnitude of this relative price effect on the demand structure is determined by the elasticity of substitution between the two sectors, which itself is controlled by the parameter γ. If the (asymptotic) elasticity of substitution between goods and services is unity (i.e. $\gamma = 0$) the demand structure is independent of the relative price $P_N(t)$. If durables and non-durables are (asymptotically) gross substitutes (i.e. $\gamma < 0$) the sector which experiences a relative price increase loses in terms of expenditure shares. With gross complements the opposite is true.

Equation (1.29) characterizes how endogenous technical change affects the price of intermediate industry i. In a given point in time τ, the growth rate of the price of industry i is given by the inverse of R&D activity in this industry (relative to the average over all industries). More formally[13],

$$\frac{\dot{p}_i(\tau)}{p_i(\tau)} = g - \frac{\dot{M}_i(\tau)}{M_i(\tau)}.$$

Consequently, the price of industry i at date t is given by the history of R&D activities up to date t. What determines the R&D activity in industry i at a given date τ? As equation (1.12) shows, this R&D activity is positively related to the number of people employed in the industry. This is a standard market size effect indicating that the incentive to innovate a new machine increases proportionally to the number of workers that use it. The number of workers in industry i is above average if the intensity, $\alpha(i)$, with which non-durable good production depends on it exceeds unity (see (A.10)). Moreover, given that industry i is, as an input, more intensively used by the non-durable sector (i.e. $\alpha(i) > 1$), the number of workers employed in this industry is increasing in the expenditure share of non-durables.

Equations (1.28) and (1.29) define a system of equations in $S_N(t)$ and $\{p_i(t)\}_{i=0}^1$. By setting t equal to zero, we obtain the initial conditions

[13] This follows immediately from (1.6) and (1.26). The average of the R&D activity over all industries shows up because of the choice of numeraire.

$$p_i(0) = 1, \ \forall i, \tag{1.30}$$

and

$$S_N(0) = \beta \left[\frac{L}{\nu - 1} + \frac{1}{(1-\epsilon)\eta} \left[\rho - \frac{\epsilon \eta L}{\nu} \right] \right]^{-\epsilon} = \beta \mathcal{E}_0^{-\epsilon}. \tag{1.31}$$

Solving the system of equations we obtain the following proposition:

Proposition 1.2. *Along the dynamic equilibrium path, the sectoral dynamics are characterized by*

$$S_N(t) = \frac{S_N(0)}{\exp\left[(\gamma\Delta + \epsilon g)t\right] + \left[\exp\left[(\gamma\Delta + \epsilon g)t\right] - 1\right] \frac{S_N(0)\gamma\eta\frac{\nu-1}{\nu}\sigma^2\mathcal{E}_0}{\gamma\Delta + \epsilon g}}, \tag{1.32}$$

where $S_N(0)$ *is given by* (1.31). *Moreover, we have*

$$P_N(t) = \exp\left[\frac{\epsilon g}{\gamma} t\right] \left(\frac{S_N(t)}{S_N(0)} \right)^{\frac{1}{\gamma}}, \tag{1.33}$$

$$L_i(t) = L + (\nu - 1)\mathcal{E}_0 \left[\alpha(i) - 1\right] S_N(t), \tag{1.34}$$

and

$$p_i(t) = \left[\frac{S_N(t)}{S_N(0)} \exp\left[(\gamma\Delta + \epsilon g)t\right] \right]^{\frac{\alpha(i)-1}{\gamma\sigma^2}}. \tag{1.35}$$

This is an equilibrium path under the parameter restrictions stated in Proposition 1.1 and as long as (1.14) *is fulfilled for all* t.

Proof. See Appendix A.1. □

Proposition 1.2 shows that we indeed obtain closed form solutions for all variables. Finally, note that we assumed that (1.14) is fulfilled along the entire path. We are now prepared to state conditions on the exogenous parameters such that this condition is indeed met. This is done in the next proposition. Recall that condition (1.14) ensures that the expenditure share devoted to non-durables does not exceed unity. As we can see from (1.32), the dynamics of $S_N(t)$ depend on several parameter values. In the following we focus on a case in which the durable good sector is asymptotically dominant, for which we get:

Proposition 1.3. *Suppose*

$$\gamma\Delta + \frac{\epsilon}{1-\epsilon}\left[\frac{\eta L}{\nu} - \rho\right] \geq 0, \tag{1.36}$$

$$\gamma\Delta + \frac{\epsilon}{1-\epsilon}\left[\frac{\eta L}{\nu} - \rho\right] > -\gamma\eta\frac{\nu-1}{\nu}\sigma^2\beta\left[\frac{L}{\nu-1} + \frac{1}{(1-\epsilon)\eta}\left[\rho - \frac{\epsilon\eta L}{\nu}\right]\right]^{1-\epsilon}, \tag{1.37}$$

and

$$\beta < \left[\frac{L}{\nu - 1} + \frac{1}{(1-\epsilon)\eta}\left[\rho - \frac{\epsilon\eta L}{\nu}\right]\right]^{\epsilon}. \tag{1.38}$$

Then, condition (1.14) *is fulfilled along the entire path and the dynamics in Propositions 1.1 and 1.2 characterize a dynamic equilibrium path.*

Proof. See Appendix A.1. □

We are now ready to discuss the equilibrium dynamics on the disaggregate level. The assumptions in Proposition 1.3 make sure that $S_N(t)$ is declining over time. An easy way to see the dynamics of $S_N(t)$ is in equation (A.13). The non-homotheticity channel leads to a declining $S_N(t)$, since non-durables are necessities by assumption and expenditures grow over time. So the conditions in Proposition 1.3 ensure that this declining trend in $S_N(t)$ due to income effects is not overturned by a relative price effects. Whether the relative price effects increases or decreases $S_N(t)$ depends on the elasticity of substitution as well as on how $P_N(t)$ changes over time. If the (asymptotic) elasticity of substitution is larger than unity (i.e. if $\gamma < 0$), an increase in the relative price, $P_N(t)$, decreases the expenditure share devoted to non-durables. With $\gamma > 0$ the opposite is true. For the growth rate of the (relative) price of the non-durable sector, we obtain (see (1.33) and (A.13))

$$\frac{\dot{P}_N(t)}{P_N(t)} = -\Delta - \eta\frac{\nu - 1}{\nu}\sigma^2\mathcal{E}_0 S_N(t). \tag{1.39}$$

The relative price changes because of the exogenous TFP growth rate difference, Δ, as well as because of industry-specific technical progress (captured by the second term in (1.39)).

With $\frac{\dot{S}_N(t)}{S_N(t)}$ being always negative the expenditure share of non-durable goods asymptotically converges to zero and the durable sector is therefore asymptotically dominant.[14] As time goes to infinity, $\frac{\dot{S}_N(t)}{S_N(t)}$ converges to $-(\gamma\Delta + \epsilon g)$, which is still negative (see assumption (1.36)). In this sense, structural change does not come to a halt and does exist even asymptotically. In contrast, since asymptotically the direction of industry-specific technical change is fully determined by the durable good sector, we have

$$\lim_{t\to\infty}\frac{\dot{P}_N(t)}{P_N(t)} = -\Delta. \tag{1.40}$$

Hence, asymptotically, the growth rate of the relative price does not change anymore (but it can differ from zero).

The theory offers relatively rich dynamics. It is worthwhile to emphasize that these

[14] Note that just the expenditure share of non-durables goes to zero. In levels non-durable good expenditures go to infinity.

dynamics occur along the equilibrium path of a dynamic general equilibrium model. Consequently there are no exogenous shifts in demand or supply. Since the (asymptotic) elasticity of substitution can be either larger or smaller then unity (i.e. $\gamma \lesseqgtr 0$) our theory does not take a stand whether the expenditure share, $S_N(t)$, increases or decreases in the relative price (see (1.17)). In addition, because there are both relative price and income effects on the expenditure structure, the elasticity of substitution between durables and non-durables is not so easy to infer. For instance, the fact that the expenditure share of non-durable goods declined whereas the relative price of non-durable goods increased over the last 80 years does not automatically imply that the elasticity of substitution has to be larger than unity. It could well be that it is strictly smaller than unity but the relative price effect on the expenditure structure is overturned by an income effect.

From (1.39) it is clear that our theory does not make a prediction about the average *level* of relative price growth (i.e. whether $P_N(t)$ is increasing or declining). Depending on the sign of Δ this can either be negative or positive. However, the theory does make a clear prediction how $\frac{\dot{P}_N(t)}{P_N(t)}$ *changes* over time: the growth rate of the (relative) price of a sector which experiences a decline in terms of its expenditure share increases over time. This is consistent with Figures 1.1 and 1.2. The reason for this dynamic is directed technical change. As the expenditure share of the non-durable sector shrinks, (1.34) shows that a declining amount of labor is allocated to industries which are relative intensively used by the non-durable sector (i.e. with $\alpha(i) > 1$). A declining market size in these sectors imply a declining R&D activity (see (A.11)) and an increasing industry-specific price growth $\frac{\dot{p}_i(t)}{p_i(t)}$. This effect constitutes the so called *market size effect*. Formally, this can be seen from combining (1.35) and (A.13) and writing the industry-specific price growth as

$$\frac{\dot{p}_i(t)}{p_i(t)} = -\left[\alpha(i) - 1\right]\eta\frac{\nu - 1}{\nu}\mathcal{E}_0 S_N(t). \tag{1.41}$$

As the price growth rate of industries that are more intensively used in the non-durable sector increases, the growth rate of the relative price of non-durables, $P_N(t)$, increases too.[15]

It is the aim of the next section to test this prediction of industry directed technical change using disaggregate US data. By doing so we explicitly make use of the input-output structure of the US economy. This allows us to identify the variation in the industrial market shares which is exogenous from the perspective of an individual firm that makes the decision of how much to invest in R&D.

[15]For this see (1.2), which implies that we have $\frac{\dot{P}_N(t)}{P_N(t)} = -\Delta + \int_0^1 (\alpha(i) - 1)\frac{\dot{p}_i(t)}{p_i(t)} di$.

1.4 Empirical Application

1.4.1 Testing for the Market Size Effect

In the following, we test for our theory's prediction how structural change in terms of *final consumption* translates into changes in the market sizes of different *industries* at the value-added level and how this in turns affects industry-specific TFP and output price growth rates. We use US data from EU KLEMS covering 30 different industries and 30 years.[16] For our analysis we build five-year spells, which leads to 180 observations. Our model's main prediction suggest a negative (positive) correlation between an industry's market size and its price (TFP) growth rate. This motivates the following regression

$$d_i(t) = \delta \log s_i(t-l) + \kappa_i + \phi(t) + u_i(t), \tag{1.42}$$

where $d_i(t)$ is one of the dependent variables (i.e. either the TFP or the price growth rate). $s_i(t-l)$ is the market size of industry i, κ_i and $\phi(t)$ represent a full set of industry and time fixed effects and $u_i(t)$ is an error term. The TFP and price growth rates, $d_i(t)$, are calculated as log-differences over the five-year interval between t and $t-5$. The market size measures the average fraction of industry value-added, va_i, relative to total GDP over a five-year interval, or formally[17]

$$s_i(t-l) = \frac{1}{5}\sum_{k=1}^{5} \frac{va_i(t-l-k)}{GDP(t-l-k)}. \tag{1.43}$$

An important question is the timing. In our theory, where all agents are perfectly forward looking and R&D investments immediately result in a TFP enhancing innovation, expenditure shares and TFP growth rates co-move instantaneously. Arguably, this is not true in reality and for this reason we explore different time lags of length of zero, one and two periods (i.e. $l = 0, 5, 10$). The industry and time fixed effects are included to control for industry-specific differences in the effectiveness of R&D investments and time trends in the average productivity growth rate.[18] Our theory of directed technical change makes a prediction about the sign of δ and this is the parameter of main interest.
Table 1.1 presents results of our baseline specification using the industry-specific price growth rate as a dependent variable. The contemporaneous logarithmized value-added

[16] A precise list of data sources can be found in Appendix A.3.

[17] Note that this allows us to interpret it directly as an industry's market share. Both terms market size and market share will be used interchangeably in the following.

[18] Note again that our theory's main prediction is about *changes* in industry-specific TFP and price growth rates and not their levels.

share shows no significant correlation with the current rate of price growth, which is displayed in column (1). However, if we take lagged market shares we see a negative correlation with the price growth rate (see columns (2) and (3) in Table 1.1). This finding might have two different interpretations. On the one hand, the evolution of market shares might not perfectly be foreseen and R&D investments might take some time to materialize. This suggests that the correlation between an industry's market size and price growth rate is zero contemporaneously, becomes negative after some years and finally attenuates again. In Appendix A.2, we show for a subset of years and industries for which we have a measure of the R&D stock, that the growth rate of the R&D stock reacts immediately (and that there is no anticipating effect). This is in line with the found lags of the effects on prices (and TFP later on).

On the other hand, the low and insignificant coefficient in column (1) could also be the result of reversed causality. Suppose the industry-specific price fluctuates for exogenous reasons. Then, if the short run elasticity of substitution is smaller than one, periods with high prices are correlated with high value-added shares. This mechanical effect runs in the opposite direction of the market size effect of induced innovation and attenuates the estimate for δ. One way to relax this problem is to use the lagged value-added share. In column (4) we include both the contemporaneous and the lagged market share and show that the coefficient of the lagged market share remains significant. This mitigates the concern that the coefficient in column (2) is driven by the mechanical contemporaneous effect as well as a serial correlation in the independent variable.

The magnitude of the estimated effect of column (2) suggests that a one percent increase in an industry's market share relative to GDP decreases the price growth rate by 0.52 percentage points over the next five years. Given the standard deviation of this variable of 21 percentage points, this is an economically significant effect.

Since there exists a strong negative correlation between the industry-specific TFP growth rates and the relative price changes, it is not surprising to find the analog positive effect of a larger market size on the TFP growth rate. Table 1.2 presents our estimates using the five-year TFP growth rates as the dependent variable. Qualitatively the same picture as in Table 1.1 remains, even though the effects are slightly smaller in magnitude and less precisely estimated.

The identification strategy of the OLS regressions relies on the assumption that firms – that make the R&D investment decision – do take the industry market size as exogenously given. However, this might not be the case. Especially, some large firms might take into account that their innovation activity can affect the industry price index and consequently their market size. Depending on the elasticity of substitution this would bias our estimate up- or downwards. To address this concern we offer an IV strategy where we instrument

Dependent variable: Price growth rate

	(1)	(2)	(3)	(4)
Log market share	0.026			0.847**
	(0.088)			(0.374)
L.Log market share		-0.522***		-1.081***
		(0.202)		(0.335)
L2.Log market share			-0.419**	
			(0.168)	
N	180	150	120	150
R^2	0.312	0.441	0.484	0.570
Method	OLS	OLS	OLS	OLS

Table 1.1: OLS regression on price growth

Notes: Standard errors are clustered at the industry level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include year fixed effects (4-6 intervals) and industry fixed effects (30 groups). The total sample period runs from 1977-2007, but observations are grouped into five-year intervals. The independent variable is averaged over five years, the dependent variable is calculated as the five-year log-difference. "L." and "L2." denotes a one and two period lag respectively (i.e. $l = 5$ and $l = 10$ in equation (1.43)).

Dependent variable: TFP growth rate

	(1)	(2)	(3)	(4)
Log market share	-0.104			-0.533**
	(0.071)			(0.260)
L.Log market share		0.241**		0.593**
		(0.119)		(0.247)
L2.Log market share			0.145*	
			(0.081)	
N	180	150	120	150
R^2	0.489	0.549	0.587	0.624
Method	OLS	OLS	OLS	OLS

Table 1.2: OLS regression of TFP growth

Notes: Standard errors are clustered at the industry level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include year fixed effects (4-6 intervals) and industry fixed effects (30 groups). The total sample period runs from 1977-2007, but observations are grouped into five-year intervals. The independent variables are averaged over five years, the dependent variable is calculated as the five-year log-difference. "L." and "L2." denotes a one and two period lag respectively (i.e. $l = 5$ and $l = 10$ in equation (1.43)).

the industry market size by its component stemming from the structural change at the final consumption level. This is in line with our theory, where structural change at the final good level trickles down – via the input-output structure of the economy – to the industry value-added level, where it determines the incentive to innovate.

Hence, in order to construct our instrument we require the US input-output tables. We first have to close the gap between purchaser's prices and producer's prices.[19] This is done by the "Personal Consumption Expenditure Bridge Table". Then the input-output tables of the year 2002 are used to calculate how much nominal value-added in industry i is needed in order to produce one US dollar sale of final consumption good j. As in the theoretical section we denote this requirement coefficient as $\alpha_j(i)$. Given the gross nominal consumption, $p_j y_j$, of 76 final consumption sectors $j = 1, ..., Q$ and these intensities $\alpha_j(i)$, we can then construct for each industry and year the "potential" market size

$$\tilde{va}_i(\tau) = \sum_{j=1}^{Q} \alpha_j(i) p_j(\tau) y_j(\tau). \tag{1.44}$$

This potential market size is the value-added that *would* have been generated in industry i if the intensities would have been the same as in the year 2002. With this potential market size we can calculate our instrument, the potential market share, as

$$\tilde{s}_i(t-l) = \frac{1}{5} \sum_{k=1}^{5} \frac{\tilde{va}_i(t-l-k)}{E(t-l-k)}, \tag{1.45}$$

where the denominator is simply total consumer expenditures $E(t-l-k) = \sum_{j=1}^{Q} p_j(t-l-k) y_j(t-l-k)$.[20] The identifying assumption of this instrument is that individual firms consider the final sales in the 76 consumption categories as exogenously given. More specifically, firms do not consider that their own R&D investments can affect the price indices of the different final consumption categories and consequently their market size. For example, the assumption is that a single tire producer takes the market size of newly sold cars as exogenously given and does not consider it to be influenceable by his own R&D investments.

Table 1.3 and 1.4 and summarize the results when we instrument the market share,

[19]The producer's price of a good is the value the producer obtains when the good leaves the factory, while the purchaser's price is the price the consumer pays in a store when buying the good. Thus, the main difference is that the later contains distribution costs (like sales tax or transportation costs) while the former does not.
A detailed application of input-output tables is found in Appendix A.3.

[20]Note that this measure of total consumer expenditures differs slightly from the one reported in the National Income and Product Accounts (NIPA) since our measure of potential market size corrects for expenditures on imported (intermediate) goods.

Dependent variable: Price growth

	(1)	(2)	(3)
Log market share	-0.210**		
	(0.096)		
L.Log market share		-0.602***	
		(0.232)	
L2.Log market share			-0.437**
			(0.199)
N	180	150	120
R^2	0.279	0.438	0.483
Method	IV	IV	IV

Table 1.3: IV regression on price growth

Notes: Standard errors are clustered at the industry level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include year fixed effects (4-6 intervals) and industry fixed effects (30 groups). The total sample period runs from 1977-2007, but observations are grouped into five-year intervals. The independent variables are averaged over five years, the dependent variable is calculated as the five-year log-difference. The Log market share is instrumented by the structural change at the final consumption good level as described in Section 1.4. First stage regression results are found in Appendix A.2. "L." and "L2." denotes a one and two period lag respectively (i.e. $l = 5$ and $l = 10$ in equation (1.43)).

Dependent variable: TFP growth

	(1)	(2)	(3)
Log market share	0.090		
	(0.102)		
L.Log market share		0.296**	
		(0.144)	
L2.Log market share			0.209**
			(0.098)
N	180	150	120
R^2	0.459	0.547	0.584
Method	IV	IV	IV

Table 1.4: IV regression on TFP growth

Notes: Standard errors are clustered at the industry level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include year fixed effects (4-6 intervals) and industry fixed effects (30 groups). The total sample period runs from 1977-2007, but observations are grouped into five-year intervals. The independent variables are averaged over five years, the dependent variable is calculated as the five-year log-difference. The Log market share is instrumented by the structural change at the final consumption good level as described in Section 1.4. First stage regression results are found in Appendix A.2. "L." and "L2." denotes a one and two period lag respectively (i.e. $l = 5$ and $l = 10$ in equation (1.43)).

$s_i(t-l)$, by our measure of potential market share.[21] The effects on both the price growth rate and the industry-specific TFP growth are slightly higher, but qualitatively they show the same, consistent pattern: the coefficients of the one period lagged variables is large and statistically significant at least at the five percent level. With a two period lag, the coefficients get smaller and the contemporaneous effects are small (and at least in the case of the TFP growth insignificant). The coefficient in column (2) of Table 1.4 suggests that a one percent increase in its market share increases the industry-specific TFP growth rate by 0.3 percentage points over the next five years. Given the average five-year TFP growth rate of 4.3 percent, this is an economically significant effect.

[21]The corresponding first stage regressions can be found in Appendix A.2.

1.5 Conclusion

This paper presented a parsimonious model of industry directed technical change where households have non-homothetic preferences. Within our theoretical framework we show how structural change at the final output level translates into structural change at the industry value-added level. In line with the directed technical change literature, the industry-specific market share is the key determinant of R&D investments. A change in households' expenditure profile leads to a systematic shift in industry-specific TFP growth rates and consequently relative prices. However, the changing relative prices themselves create a feedback effect on households' expenditure structure. Hence, our model also incorporates the relative price channel of structural change. Although replicating this rich disaggregate structure, the model features constant growth on the aggregate and has a closed form solution.

Building on our theoretical model, we evaluated the market size effect empirically. Working with input-output tables, we constructed a measure of market size that is driven by an arguably exogenous component of structural change at the final output level. Our identification strategy then allowed us to evaluate the importance of the market size hypothesis across the complete set of US industries. Robust to different specifications, we find that a one percent increase in an industry's market share increases its TFP growth rate by about 0.3 percentage points or equivalently reduces its price growth by -0.6 percentage points (over a five year period). Consistent with our expectation, we also document that while R&D investments react simultaneously to an increase in market size, it takes about five years for these investments to result in larger TFP growth rates and falling prices.

Our results can be read as a qualification to the "Baumol's cost disease", which states that with an elasticity of substitution smaller than unity, sectors with a lower TFP growth rate account for an increasing fraction of total GDP and consequently, the economy's aggregate growth rate declines as sectors with lower technical progress constitute a larger fraction of the economy. Our qualification is twofold: first, we emphasize the non-homotheticity of preferences as a driver of structural change. If the production process of luxuries (with an expenditure elasticity of demand larger than one) exhibited faster technical change, there might be no cost disease – even if the elasticity of substitution were less than unity. The second challenge is due to the endogenous direction of technical change. If – as our results suggest – bigger markets attract more R&D investments, the TFP growth rate of faster expanding sectors will endogenously increase. Consequently, the ranking of the sectors along the rate of technical progress is not stable over time. The sectors that feature today a low rate of technical change and account for an increasing fraction of GDP might transform into tomorrow's engine of technical progress.

A version of this paper was submitted to the *Economic Journal* in February 2014.

2 Employment Polarization and the Role of the Apprenticeship System

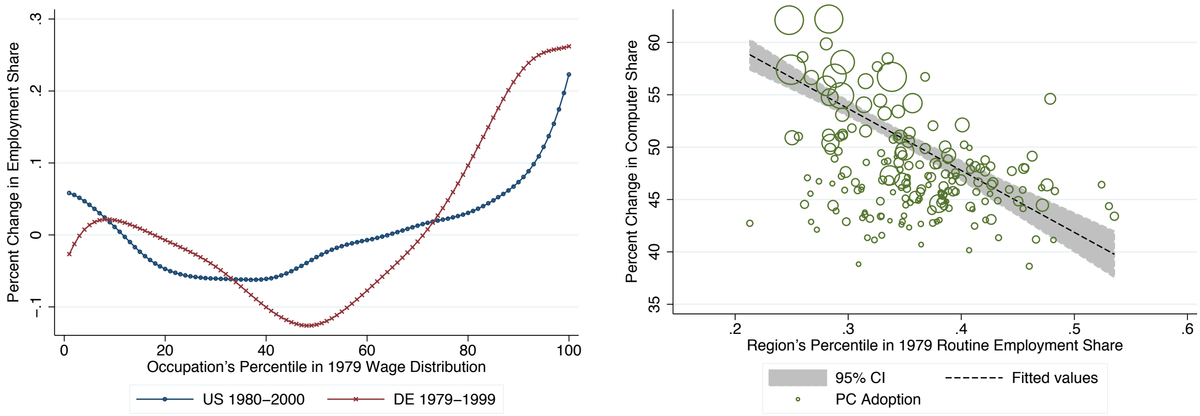
Joint with Michelle Rendall

2.1 Introduction

One of the most significant changes in the labor market has been the increasing adoption of computer technology since the 1970s (Autor *et al.*, 1998). Recent research has highlighted one specific impact of this ICT innovation: the displacement of middle income employment by capital adoption. This labor-capital displacement has caused employment polarization, which has become a major focus of research in developed economies. For example, Autor *et al.* (2003) first documented the effect of computers, not only complementing the high-skilled, but also replacing middle-skilled jobs in the US. The authors decompose occupation requirements into three task types: manual (hand and finger dexterity), routine (repetitive) and abstract (analytical). Generally, the low, middle and high portions of the income distribution are linked to manual, routine and abstract tasks, respectively. Thus, computers most easily replace middle-skill tasks. Goos *et al.* (2011) document similar employment polarization across Europe. Figure 2.1a shows the change in employment shares for the US and Germany along the 1979 wage distribution for each country.[1] As polarization is present in both countries, it seems natural to conjecture that both countries have seen a rise in polarization driven by technical change in ICT (information and communications technology). However, graphing computer adoption rates against the share of routine-intensive employment across German labor market regions (see Figure 2.1b) presents a puzzle in terms of the polarization hypothesis.[2] In Germany regions with the most computer adoption since the 1980s are those regions with the lowest routine employment share in 1979. In contrast, regions in the United States with the highest routine employment share have experienced the largest per capita computer adoption rate (Autor and Dorn, 2013, see Table 3).

[1]Information about the data sources is found in Section 2.3 and in Appendix B.2.

[2]For details on regions in Germany and the construction of routine employment see Section 2.3.



(a) Employment Polarization (b) Computer Adoption

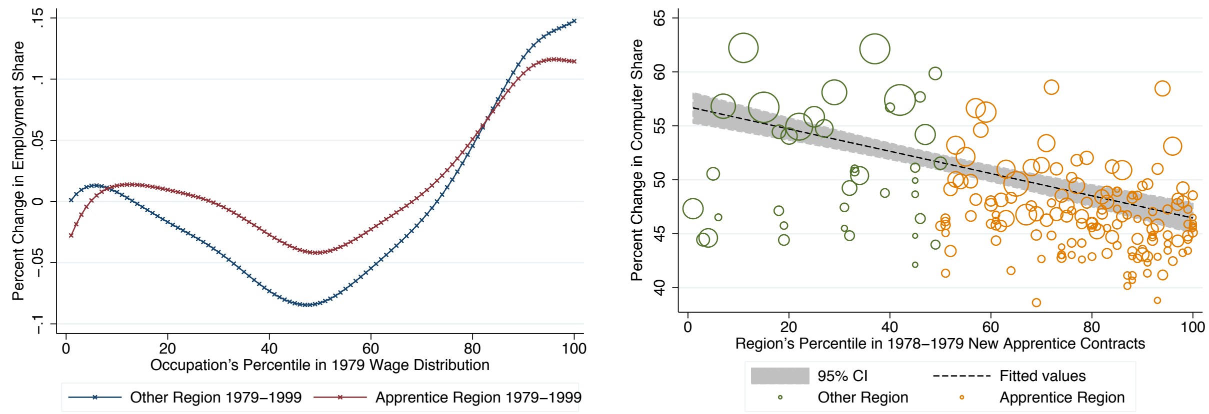
Figure 2.1: **Employment Polarization and Computers**

In this paper we argue that differences in educational systems can resolve this puzzle. More precisely, we formalize the link between worker replacement, technology adoption and an education system that incentivizes skill-specific vocational education versus general education. To support this mechanism, we use empirical evidence on the (dual-) apprenticeship system in Germany and regional variation in apprenticeship intensity. In Germany, routine-intensive local labor markets have a large, apprentice-trained labor force. We show that these local markets see less computer adoption, but also less employment polarization over time. Figure 2.2b sorts regions along the percentile distribution in terms of new apprenticeship contracts in 1978/79 and graphs the share of personal computers used within each region.[3] The graph shows that regions with above average rates of new apprenticeship contracts in the 1978-1979 period (labeled "Apprentice Regions"), are also regions with lower computer shares in 1999. In fact, the linear fit suggests a negative correlation of -0.445.

Figure 2.2a repeats Figure 2.1a for Germany by regions with above and below average new apprenticeship contracts from 1978 and 1979. Regions with above average ratios in apprenticeship contracts (or apprentice-intensive regions) have experienced significantly less employment polarization. That is, regions with little employment polarization are also regions with less computer adoption.

At the same time, Autor and Dorn (2013) find that the rise in the service sector has come with large wage polarization in the US. That is, jobs in the middle of the wage distribution are replaced by growth in low wage service sector jobs leading to greater wage inequality. In comparison, structural transformation (or the rise of the service sector), has been considerably slower in Germany. In 1980 roughly 50 percent of Germany's em-

[3]New apprenticeship contracts are measured as the ratio of new contracts over the employed population within local German labor markets.



(a) Employment Polarization by Apprentice Intensity

(b) Computer Adoption by Region and Apprentice Intensity

Figure 2.2: **Employment Polarization and Computers across Regions**

ployment was manufacturing related (including agriculture), with this number dropping to roughly 38 percent in 2000. In contrast, the US employment share in manufacturing fell from 34 to 25 percent during the same period. In terms of employment polarization both Germany and the US have seen an increase at the top of the distribution. However, only the US has a marked U-shape with low wage occupations growing over time.

We are not the first to make a link between education systems and cross-country growth differences. Goldin and Katz (2008) hint that slower output growth in Europe could be a function of the vocational education emphasis, rather than general education as in the US. Krueger and Kumar (2004) formalize this argument and suggest that since the 1980s Europe has lagged behind in terms of manufacturing productivity, investment in ICT, and/or in total output growth due to vocational education systems. However, to the best of our knowledge, we are the first to linking the education system and technology adoption to the recent literature on task based production and employment polarization (see Acemoglu and Autor, 2011, for a detailed survey).

The (dual) apprenticeship system incentivizes firms to invest in the industry- or firm-specific human capital skills of its workforce. Winkelmann (1997) documents that very few workers enter the labor market in Germany without having received specific vocational training. He further suggests that the institutional structure that allows the apprenticeship system to function in Germany is likely not present in the US. That is, the greater labor mobility, flexibility in wages and reduced layoff costs in the US make it riskier for firms to train workers in case of "poaching". Acemoglu and Pischke (1998) show that the US is characterized by a high-turnover, low-training equilibrium. Thus, high school graduates (e.g., associate degree holders or college dropouts) in the US are individuals that acquire general human capital at school, but receive very little specific training. In contrast, German apprentices acquire specific skills and tend to be more productive than those without industry-specific training when operating machinery and attending to production processes. Skills are specifically learned during the training period and not later, as apprentices have higher wages then unskilled workers in Germany, but have almost no return to experience and tenure within the firm (for empirical evidence see Adda *et al.*, 2006; Hanushek *et al.*, 2011). In summary, German non-college graduates are composed primarily of skilled apprentices who have acquired specific skills at the expense of firms/governments.

These apprenticeship costs, estimated to be about €15,000 per year per apprentice by the *Bundesinstitut fuer Berufsbildung* (BiBB), are, similarly to technology adoption, mostly born by firms (Harhoff and Kane, 1993; Soskice, 1994). From the firm's perspective then, acquiring new machinery in areas where apprentices are employed is more costly because the prior training (specific skill) becomes obsolete and the comparative advantage acquired through specific training during the apprenticeship is lost. Moreover, if ICT capital replaces non-college workers (as suggested by Autor *et al.*, 2003), firms in Germany, when compared to the US, have less incentives to adopt new technology and machines and as a consequence, less middle-skilled jobs are destroyed in Germany. Finally, Michaels *et al.* (2010) document the positive correlation between high-skill demand/ high-skilled wages and ICT adoption across countries, and van Ark *et al.* (2003) show that the EU is "lagging" behind the US in terms of ICT capital adoption. Although non-ICT adoption is very high in Europe, ICT has diffused slowly with no "catch up" effect observed - in reality the gap between the EU and US has even widened.

In this paper, we develop a simple "task-replacing" model a la Acemoglu and Autor (2011) to demonstrate how non-college, routine task labor is prone to substitution by capital/machines. In addition to the substitutability of ICT and non-college labor the model also incorporates the concept of complementarities between college labor and ICT. Building on the empirical fact that apprentice-skills are immobile, we extend the model to a spatial equilibrium setting where local labor markets have differential degrees of skill-specific workers (apprentices) similar to Autor and Dorn (2013). The regional analysis provides results across local labor markets that follow the German commuter zones. It predicts that regions using apprentices (i.e., non-college labor with task-specific human capital, instead of general workers): (1) adopted fewer computers; (2) face slower employment polarization or displacement of routine tasks; and (3) realize a slower rate of structural transformation, or a smaller rise in low-skilled services, since apprentices primarily work in the manufacturing sector (i.e. slower employment polarization). We then evaluate these hypotheses using German social security data.

Although Germany has an extensive apprenticeship system there exists substantial variation in regional apprenticeship intensity. Before the ratification of the *Berufsbildungsgesetz* at the beginning of the 1970s and the introduction of the *Ausbildungsplatzfoerderungsgesetz* in 1976 the German apprenticeship system was regionally fragmented. Only after the two oil shocks and the following deterioration of employment opportunities for young adults, the federal government made an effort in promoting the apprentice-system within Germany and with it provided a systematic federal structure (or incentives) to educate the workforce.[4] Thus, in our empirical analysis, we use initial regional variation in apprentice shares and routine employment shares to determine the interaction between education, ICT adoption and labor market polarization. Exploiting regional variation within a country, rather than using cross-country variation, avoids accounting for a myriad of other potential important cultural and institutional differences.

The empirical results for Germany confirm the model's hypotheses, that is, regions with high apprenticeship rates have less computer adoption, less employment polarization and a smaller rise in service employment. The results for other (non-apprentice) routine-labor are similar in magnitude, in terms of labor displacement, to the US results for the decades from 1980 to 2000. That is, a region with 10 percentage points more routine-labor has a 2.19 percentage points larger displacement of routine-labor per decade. The results on computer adoption and service employment are in the same direction as in the US but smaller in magnitudes.

The remainder of the paper is organized as follows: Section 2.2 presents the theoretical model and derives the testable implications. Section 2.3 provides the German data description with aggregate and regional facts. Section 2.4 presents the empirical results and compares them both across regions within Germany and in an international context. Lastly, Section 2.5 concludes.

2.2 The Model

To model the interaction between apprenticeships and technological change, we develop a partial equilibrium model. Assume skill supplies are given, and the population is divided into non-college (apprentice or general education) and college graduates.[5] For simplicity,

[4]See Casey, 1991; and see BiBB, 1977; Soskice, 1994 and references therein for a detailed discussion of the history of the apprenticeship system in Germany.

[5]For simplicity we assume skill supplies to be fixed. Incorporating an endogenous education decision does not change the results of employment polarization qualitatively.

we refer to non-college workers as low-skilled and college graduates as high-skilled.[6] Firms choose how many machines to purchase for production and which type of worker to use for what task. Machines are produced by monopolists each period and technological progress is exogenous.

Final Good Production

The model is loosely based on Acemoglu and Autor (2011) and Acemoglu and Zilibotti (2001), but with the addition of apprentices. The unique final good is made up of a continuum of intermediate goods, $[0, 1]$,

$$Y_t = \exp\left[\int_0^1 \ln y_t(i) di\right].$$

We normalize the price of the final good to one each period. Each good can be produced using machines and both types of labor,

$$y_t(i) = \max\{\alpha_\ell(i), \mathbb{1}_{(\ell=a|i\geq \underline{x})}\hat{\alpha}_\ell(i)\}\ell_t(i) + (\alpha_h(i)h_t(i))^\beta \left[\int_0^{N_t} (\alpha_k(i))^\beta (k_t(i,v))^{1-\beta}\, dv\right],$$

where $\alpha_j(i) > 0$ captures the *skill-specific and task-specific* comparative advantage in producing good i. The specific productivity skills of apprentices, $\mathbb{1}_{(\ell=a|i\geq \underline{x})}$, in contrast to "regular" low-skilled workers, ℓ_t, are captured by $\hat{\alpha}_\ell(i)$. Hence, if the low-skilled are apprentices, they have productivity, $\hat{\alpha}_\ell(i) > \alpha_\ell(i)$.[7] However, apprentices are more productive only for a subset of tasks, $i \geq \underline{x}$.[8] The high-skilled productivity in contrast is constant across all goods, $\alpha_h(i) = \alpha_h \;\forall\, i \in [0, 1]$, but requires capital, $k(i, v)$, to be productive.[9] Finally, capital's productivity varies over the interval, $\alpha_k(i)$.[10]

[6]These labels do not imply that the low-skilled acquire no skills, rather they acquire different skills, as the skill set is lower in terms of formal schooling only. Since this paper's focus is *not* on wage polarization, we abstract from a third skill type.

[7]This Assumption is a reduced form of modeling the firms' decision to invest in teaching apprentices a task-specific skill. Due to labor market imperfections, such as high firing cost, the German firm has a monopsony power over its apprentices, giving the incentives to invest in apprentices' costly training (Acemoglu and Pischke, 1998).

[8]Very low-skill jobs, e.g. cleaning occupations, do not require a special apprenticeship training to be done. Moreover, the relative wage differential between apprentices and non-apprentices suggests an apprentice's comparative advantage to be largest in middle-skill occupations.

[9]The results depend only on the relative productivities of the low-skilled and machines in the *RT* sector.

[10]The power of the β component serves as a convenient normalization.

Definition of Tasks

Each intermediate good has manual-, routine- and abstract-task components and intermediate goods can be sorted according to these components. We sort goods on the interval $i \in [0,1]$ from mostly manual to abstract, with routine in the middle. That is, the manual-intensive component is decreasing over the unit interval. The routine-intensive component is an inverted U-shape on the interval of intermediate goods. Thus, only goods in the middle have a large routine component that is easily replaceable by machines. The abstract component is increasing over the unit interval and goods at the upper range are mostly abstract.

Denote production processes at the low-end, $i \in [0, \underline{x})$, as low-skilled service occupation, LST. Denote the interval with a large routine component as, $RT = [\underline{x}, \overline{x}]$. For these production processes apprenticeships provide extra training yielding additional productivity. The routine component of these tasks can be done by labor or machines. At the upper range, $i \geq \overline{x}$, tasks are abstract and complex and the high-skilled are most productive. However, high-skilled labor requires machines to preform these tasks. The following Assumption formalizes this idea in terms of comparative advantages.

Assumption 2.1.

$\frac{\alpha_\ell(i)}{\alpha_h}$ is continuously differentiable and strictly decreasing in i. In addition, assume that machine productivity is highest in routine tasks, i.e. $\frac{\partial \alpha_k(i)}{\partial i} < 0 \, \forall i \, [0,1]$.

Furthermore, it is assumed that the more abstract a production process is, the more difficult it is for low-skilled labor to be productive. Assumption 2.2 summarizes this concept.

Assumption 2.2.

Assume that $\frac{\partial^2 \alpha_\ell(i)}{\partial i^2} < 0 \, \forall i \, [0,1]$.

Given Assumption 2.1, there will be perfect sorting between between low- and high-skilled labor. Denote the threshold of sorting by J_t. Since we are interested in studying the effect of technology replacing routine-labor, Assumption 2.3 guarantees that the economy's starting point is within the potential replacement/displacement region.

Assumption 2.3.

The threshold on labor is within the RT regions for all time-periods, $J_t \in [\underline{x}, \overline{x}] \, \forall t$.

Lastly, for simplicity of derivations below, we assume that $\alpha_k(i)$ takes two distinct values, such that Assumption 2.1 is still satisfied,

Assumption 2.4.

The productivity of capital is larger on the RT interval than for tasks above this interval. That is, $\alpha_k(i) = \alpha_{k1} \equiv 1 \, \forall i \, [\underline{x}, \overline{x}]$ *and* $\alpha_k(i) = \alpha_{k2} < 1 \, \forall i \, (\overline{x}, 1]$.

Machine Production

Assume the level of technology, N_t, is exogenously given (e.g. adopted from the world technological frontier). The market for machines is perfectly competitive, such that the price must equal the marginal cost of each machine. For all machines, it requires $(1 - \beta)$ units of intermediate good $y_t(i)$ to produce one machine. Each machine is task-specific. The firm producing machines solves,

$$\max_{k_t(i,v)} p_t^k(i,v)k_t(i,v) - (1-\beta)p_t(i)k_t(i,v).$$

The price, $p_t^k(i,v) = p_t^k(i) = (1-\beta)p_t(i)$, follows immediately from the zero-profit condition.

2.2.1 The Static Equilibrium

In this Section we analyze the static equilibrium without apprentices, instead concentrating on the productivity schedule $\alpha_\ell(i)$ for the general-education low-skilled.

Given comparative advantages from above and Assumption 2.1, the economy has perfect sorting, with low-skilled labor working in the interval $[0, J_t)$, and the high-skilled and machines, k_t, working in the interval $[J_t, 1]$. Lemma 2.1 summarizes this production structure.

Lemma 2.1. *In any equilibrium, there is a threshold,* J_t*, s.t.* $\underline{x} < J_t < \overline{x}$ *and for any* $i < J_t$, $h_t(i)$, $k_t(i,v) = 0$*, for any* $i \geq J_t$, $\ell_t(i) = 0$.

Production

Producers of the final good are price takers and maximize profits, taking the price of their product $(p_t(i))$, wages $(w_{\ell t}, w_{ht})$ and the price of machines $(p_t^k(i,v))$ as given. Maximizing profits gives the demand for intermediate machines for each vintage type, v, and for each intermediate good, i,

$$k_t(i,v) = \alpha_h \alpha_k(i) h_t(i).$$

The demand for machines at each production process i is,

$$k_t(i) = \int_0^{N_t} k_t(i,v)dv = \alpha_h \alpha_k(i) h(i) N_t.$$

Given the demand for machines and Lemma 2.1, the production of tasks $y_t(i)$ is,

$$y_t(i) = \alpha_\ell(i)\ell_t(i) \quad if \;\; 0 \leq i < J_t$$
$$y_t(i) = \alpha_h \alpha_k(i) h_t(i) N_t \quad if \;\; J_t \leq i \leq 1.$$

In any equilibrium, the marginal product of each skill group has to be equalized across all tasks performed by a given group. This means price differences must exactly offset productivity differences,

$$p_t(i)\alpha_\ell(i) = p_t(i')\alpha_\ell(i') := P_{\ell t}, \tag{2.1}$$

and

$$p_t(i)\alpha_h\alpha_k(i) = p_t(i')\alpha_h\alpha_k(i') := P_{ht}. \tag{2.2}$$

No Arbitrage Condition across Skills

Due to the Cobb-Douglas production structure, expenditures, $p_t(i)x_t(i)$, are equalized across all tasks, which implies that the low- and high-skilled are equally distributed across tasks, $\ell_t(i) = \frac{L_t}{J_t}$ and $h_t(i) = \frac{H_t}{1-J_t}$. Hence, the following cost condition must hold in equilibrium,

$$\frac{P_{ht} H_t N_t}{1-J_t} = \frac{P_{\ell t} L_t}{J_t}.$$

Substituting prices from equations (2.1) and (2.2) yields the "no arbitrage" condition, which pins down the equilibrium threshold,

$$\frac{\alpha_h \alpha_k(J_t) H_t N_t}{1-J_t} = \frac{\alpha_\ell(J_t) L_t}{J_t}. \tag{2.3}$$

Note that the model bears also implications for wages. However, as the study of wages in Germany is beyond the scope of this paper due to the country specific issues outlined in Section 2.4.4, the wage implications are omitted here.

2.2.2 Technical Progress

To analyze the dynamics of employment and structural change in the event that new technologies are invented, assume the world technological frontier advances at the exogenous rate $(1+\gamma) > 1$ or $N_t = (1+\gamma)^t N_0$ with $N_0 = 1$. That is, the technical knowledge up to the frontier is assumed to be perfectly available to each producer, whereupon he decides on how much to invest in machines of this technology.

Employment Division

Let productivity differences between the low-skilled and the high-skilled (that use machines) be $\omega(i) \equiv \ln(\alpha_\ell(i)) - \ln(\alpha_h \alpha_k(i))$. Consider a one-time change in N and totally differentiate the no arbitrage condition in equation (2.3) with respect to N_t,

$$\frac{dJ_t}{d\ln(N_t)} = \left(\frac{\partial \omega(J_t)}{\partial J_t} - \frac{1}{1-J_t} - \frac{1}{J_t}\right)^{-1} < 0, \tag{2.4}$$

where by Assumption 2.1, $\omega' < 0$. Driven by skill-biased technical change, the range of tasks performed by high-skilled workers increases at the expense of low-skilled workers. From the threshold cross-derivative - under Assumptions 2.1 and 2.2 - the negative growth in the threshold accelerates the lower the threshold becomes,

$$\frac{d^2 J_t}{d\ln(N_t) dJ_t} = -\left(\frac{dJ_t}{d\ln(N_t)}\right)^2 \left(\frac{\partial^2 \omega(J_t)}{\partial J_t^2} + \frac{1-2J}{(J_t(1-J_t))^2}\right) > 0 \text{ for all } \; J_t > J^\star, \tag{2.5}$$

if the threshold is above a certain critical value, $J^\star$, where $J^\star \in \left(0, \frac{1}{2}\right)$.[11] Initially it is very costly to spread high-skilled labor over more tasks and acquire the necessary machines for labor to be productive. However, the marginal cost of spreading high-skilled labor over evermore tasks decreases with the threshold. Every additional task, is more marginal. I.e., spreading high-skilled labor from one to two tasks, is more costly, than spreading it from two to three tasks.

Machine Investment

To derive the effect of technological innovation on total machine investment, let us define the demand for machines as X_t. Then X_t is given by,

$$X_t = \int_{J_t}^{1} \int_{0}^{N_t} k_t(i,v) dv di = \alpha_h N_t \frac{H_t}{1-J_t} \int_{J_t}^{1} \alpha_k(i)\, di. \tag{2.6}$$

Given Assumption 2.4, this simplifies to

$$X_t = \alpha_h N_t \frac{H}{1-J_t} \left[(\overline{x} - J_t) + (1-\overline{x})\, \alpha_{k2} \right]. \tag{2.7}$$

[11]See Appendix B.1 for the derivation of $J^\star$.

New technologies, a rise in N_t, increase machines' relative productivity and firms adopt more machines,

$$\frac{d\ln(X_t)}{d\ln(N_t)} = \frac{\partial \ln(X_t)}{\partial \ln(N_t)} + \frac{\partial \ln(X_t)}{\partial J_t}\frac{dJ_t}{d\ln(N_t)} > 0. \tag{2.8}$$

The first term is the direct productivity effect, each tasks uses more machines. The second term is the indirect effect, more tasks are done by machines. Since the direct effect is always positive and irrespective of the threshold, the following analysis only focuses on the second term. The effect of a change in the threshold on machine adoption is,

$$\frac{\partial \ln(X_t)}{\partial J_t}\frac{dJ_t}{d\ln(N_t)} = -\frac{dJ_t}{d\ln(N_t)}\left(\frac{1}{\overline{x} - J_t} - \frac{1}{1 - J_t}\right) > 0. \tag{2.9}$$

There are two effects, (1) the interval in which machines are used increases and routine-labor is replaced (i.e. J_t decreases); but (2) each machine is used by less high-skilled labor (the last term in equation (2.9)). Given Assumption 2.4, machines are more productive in the RT-interval, the first effect always outweighs the second, within the routine-intensive interval.

Routine-labor Displacement

Define the labor share performing routine occupations as $L_{RT,t} := \frac{L_t}{J_t}(J_t - \underline{x})$. The interval, $(J_t - \underline{x})$ is a subset of the total interval of RT, $(\min\{J_t, \overline{x}\} - \underline{x})$. Strictly speaking, the model suggests that the high-skilled and machines perform all tasks in the interval $i \in [J_{h,t}, 1]$, even though machines become increasingly productive at more routine tasks. Therefore, routine-labor would also include high-skilled labor by Assumption 2.3. However, recall that each task i, has three components: manual, routine and abstract. If there is only labor in the interval, we could imagine that labor does all three components at the same time. That is, a secretary does manual, as well as routine and abstract tasks for the production of intermediate good $i = j$. However, if there is both labor and machines, the routine component of production from $i \in [J_t, \overline{x}]$ might always be performed by machines and the non-routine component by high-skilled labor. E.g., the addition and subtraction of numbers are performed by machines and the more analytical tasks are performed by high-skilled labor using machines. Therefore, we abstract from high-skilled labor in the RT interval.[12] With technical progress and Assumptions 2.1 and 2.3, the change in

[12] Alternatively, we could write a model combining the pure substitution effect of machines and middle-skilled tasks as in Acemoglu and Autor (2011) and the complementarity between machines and high-skilled tasks, as in Acemoglu and Zilibotti (2001). Since this is a stylized model, we choose to keep a simpler approach of only modeling one part explicitly.

routine-labor is,

$$\frac{\partial \ln L_{RT,t}}{\partial J_t}\frac{dJ_t}{d\ln(N_t)} = \left(\frac{\underline{x}}{(J_t-\underline{x})J_t}\right)\frac{dJ_t}{d\ln(N_t)} < 0. \tag{2.10}$$

Technological progress leads to a fall in routine employment. As some labor shifts to the production of low-skilled goods, $i < \underline{x}$, the relative fall in the number of routine tasks is always larger than the increase in the number of workers per task.

Low-skilled Service Sector Employment

Finally, as in Autor and Dorn (2013), the displacement of labor to production processes below $\underline{x}$ implies that employment in low-skilled services increases upon ICT capital adoption by,

$$\frac{\partial \ln(L_{LST,t})}{\partial J_t}\frac{dJ_t}{d\ln(N_t)} = -\frac{1}{J_t}\frac{dJ_t}{d\ln(N_t)} > 0, \tag{2.11}$$

where labor in low-skilled services, $L_{LST,t} := \frac{L_t}{J_t}\underline{x}$, is all labor in the interval of $LST = [0, \underline{x}]$.

The Effects of Technical Progress

Proposition 2.1 summarizes the effects of technological progress on machine adoption and the allocation of labor.

Proposition 2.1. *Upon arrival of new (ICT) technologies, a rise in N_t causes:*

1. *the adoption of more machines;*
2. *the displacement of labor in routine tasks; and*
3. *an increase of low-skilled service labor.*

2.2.3 Spatial Equilibrium

To discuss differences across apprentice-intensive and general-education regions, we introduce an integrated spatial equilibrium model without labor mobility.[13] Following Autor and Dorn (2013), we assume that goods from each region are perfect substitutes, which ensures that goods' prices are equated in equilibrium. Moreover, since there is only one

[13]Dustmann and Pereira (2008) show that job mobility (wage growth and returns to experience) is substantially lower in Germany compared to the UK. Adda *et al.* (2006) further document that especially apprentices are less mobile and again overall job mobility is substantially lower in Germany compared to the US. Since job mobility is a prerequisite for regional mobility, these facts also hint to low overall mobility in Germany.

tradable commodity, there are no gains from trade and no trade will take place in equilibrium.

Consider two types of regions. Regions have either only apprentices or only low-skilled workers. Since apprenticeship training is local (firm-specific) and apprentices exhibit little mobility we assume the low-skilled, L_t, have additional productivity, captured in $\hat{\alpha}_\ell(i)$, in the apprentice only regions.[14] The only difference between an apprentice region and others is the relative productivity of the low-skill group and $\hat{\alpha}_\ell(i) > \alpha_\ell(i)$. Denote the "specific apprentice productivity" as λ, where $\hat{\alpha}_\ell = f(\alpha_\ell, \lambda)$ and $\frac{\partial \hat{\alpha}_\ell}{\partial \lambda} > 0$. *Ceteris paribus* a region with apprentices has a higher threshold J_t,

$$\frac{dJ_t}{d\lambda} = -\frac{1}{\hat{\alpha}_\ell(J_t)} \frac{\partial \hat{\alpha}_\ell(J_t)}{\partial \lambda} \frac{dJ_t}{d\ln(N_t)} > 0. \tag{2.12}$$

For the purpose of this study, $\hat{\alpha}_\ell(i)$ can take any functional form as long as (1) Assumptions 2.1 and 2.2 are satisfied; and (2) regions with apprentices have a slower fall in the threshold upon technology adoption,

$$\frac{d\frac{dJ_t}{d\ln(N_t)}}{d\lambda} > 0, \tag{2.13}$$

or

$$\left(\frac{d^2\omega(J_t)}{dJ_t^2} + \frac{1-2J}{(J_t(1-J_t))^2}\right) \frac{1}{\hat{\alpha}_\ell(J_t)} \frac{d\hat{\alpha}_\ell(J_t)}{d\lambda} \frac{dJ_t}{d\ln(N_t)} > \frac{d^2\omega(J_t)}{dJ_t d\lambda}. \tag{2.14}$$

Proof. See Appendix B.1. □

The left hand side is strictly positive as long as $J_t > J^\star$ (see equation (2.5)) and hence the condition holds whenever $\frac{d^2\omega(J_t)}{dJ_t d\lambda} < 0$. One simple productivity schedule that fulfills this condition is $\hat{\alpha}_\ell(i) = \alpha_\ell(i) \cdot \lambda(i)$ with $\frac{\partial \lambda(i)}{\partial i} < 0$. The qualitative results are independent of the exact $\hat{\alpha}_\ell(i)$-schedule, as long as equation (2.14) holds. For the remainder of the paper it is assumed that equation (2.14) is satisfied.

Given this productivity schedule, the differential behavior of apprentice- versus other regions with respect to (1) machine adoption, (2) routine-labor displacement, and (3) low-skilled service growth can be studied. The cross derivatives of equations (2.9), (2.10) and (2.11) with respect to the apprentice productivity, λ, summarize the relevant effects.

[14] Alternatively, instead of different regions, the thought experiment also works across occupations which are differentially prone to apprentice employment.

Machine Adoption across Regions

From equation (2.9), technology innovation leads to a rise in machine adoption. The differential effect of machine adoption across regions is,

$$\frac{d\left(\frac{\partial \ln(X_t)}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{d\lambda} = \frac{\partial\left(\frac{\partial \ln(X_t)}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{\partial J_t}\frac{dJ_t}{d\lambda} + \frac{\partial\left(\frac{\partial \ln(X_t)}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{\partial \lambda} < 0. \tag{2.15}$$

Using the results from equations (2.4), (2.5), (2.12), condition (2.14) and Assumptions 2.1 - 2.4 apprentice-regions have less machine adoption given a threshold in the RT-region, $J_t > J^{\star}$.[15] The differential speed of machine adoption across regions is *only* driven by differences in the substitution channel (of the low-skilled). The complementarity effect, conditional on regions having the same high-skilled labor share, is identical in apprentice- and other regions.

Proof. See Appendix B.1. □

Routine-labor Displacement across Regions

Analogously to above, differentiating equation (2.10) with respect to the apprentice productivity, λ,

$$\frac{d\left(\frac{\partial \ln L_{RT,t}}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{d\lambda} = \frac{\partial\left(\frac{\partial \ln L_{RT,t}}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{\partial J_t}\frac{dJ_t}{d\lambda} + \frac{\partial\left(\frac{\partial \ln L_{RT,t}}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{\partial \lambda} > 0, \tag{2.16}$$

shows the impact of apprentices. That is, with the results from equations (2.4), (2.5), (2.12), condition (2.14), and Assumptions 2.1 - 2.4, as long as $J_t > J^{\star}$, technical progress in apprentice-regions leads to less displacement of routine employment. Intuitively, apprentices are more productive than other low-skilled workers and, therefore, the opportunity cost of replacing them is larger.

Proof. See Appendix B.1. □

Low-skilled Service Employment Across Regions

The derivation of differential growth in low-skilled services is analogous to routine-displacement above. That is, low-skilled service employment, $L_{LST,t}$ increases faster for non-apprentice

[15] Technically, this still holds for thresholds below $J^{\star}$, as long as the absolute value of the first term is larger than the second term.

regions,

$$\frac{d\left(\frac{\partial \ln L_{LST,t}}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{d\lambda} = \frac{\partial\left(\frac{\partial \ln L_{LST,t}}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{\partial J_t}\frac{dJ_t}{d\lambda} + \frac{\partial\left(\frac{\partial \ln L_{LST,t}}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{\partial \lambda} > 0, \tag{2.17}$$

given equations (2.4), (2.5), (2.12), condition (2.14) and Assumptions 2.1 - 2.4, as long as $J_t > J^\star$. As less routine-labor is replaced by machines in apprentice-intensive regions, there is also displacement to low-skilled services.[16]

Proof. See Appendix B.1. □

2.2.4 Testable Implications and Empirical Specification

Using the results from equations (2.15)-(2.17), we derive three testable implications across German commuting zones. The testable implications relate to: (1) the adoption of machines; (2) the rate of displacement of routine-labor; and (3) the increase in low-skilled service labor.

Empirical Specification

The data does not provide a direct measure of technological change, N_t. In the model, the change in the threshold parameter, J_t only changes because of technological progress, therefore,

$$\frac{dJ_t}{d\ln(N_t)} \equiv \frac{dJ_t}{dt}.$$

Then the effects of technology on the dependent variable, $Y_t \in \{X_t; L_{RT,t}; L_{LST,t}\}$, from equations (2.9)-(2.11), are

$$\frac{\partial \ln(Y_t)}{\partial J_t}\frac{dJ_t}{d\ln(N_t)} \approx \frac{\Delta \ln(Y_t)}{\Delta J_t}\frac{\Delta J_t}{\Delta t}.$$

Ignoring apprentices, the change in J_t over time only depends on the region's *initial* J_0. That is, conditional on J_0, regions have the same change in the threshold value and hence in the dependent variable,

$$\frac{\Delta \ln(Y_t)}{\Delta J_t}\frac{\Delta J_t}{\Delta t} \equiv \Delta(\ln(Y_t) - \ln(Y_0))\Big|_{J_0}.$$

Thresholds, J_t, are an abstract concept and not observed in data. However, a region's routine-labor share is observable, $L_{RT,0}$. The routine-labor share is determined by the

[16]The effect on low-skilled service employment is equal in magnitude (in levels) to the (negative) effect on routine-labor.

threshold, that is the higher the threshold, the higher the routine-labor share. Hence, the threshold can be replaced by the routine-labor share, $L_{RT,0}$, yielding

$$\Delta(\ln(Y_t) - \ln(Y_0))\Big|_{J_0} \approx \Delta(\ln(Y_t) - \ln(Y_0))\Big|_{L_{RT,0}}.$$

Ignoring any productivity differences between apprentices and other low-skilled labor, since all regions face the same global technology, the initial routine-labor share, $L_{RT,0}$, captures all the variation in the threshold, J_0 (given the two types of labor, low- and high-skilled must equal one). Therefore, the baseline regressions corresponding to equations (2.9)-(2.11) are,

$$\Delta \ln(Y_{t,j}) = \beta_0 + \beta_1 L_{RT,0,j} + \epsilon_j. \tag{2.18}$$

When differentiating between apprentices and other low-skilled labor, the routine labor share, $L_{RT,0}$ does not uniquely define the threshold, J_0. That is a region's threshold is determined by (1) the share of high-skilled labor and (2) the composition of low-skilled labor (apprentices or others). Only conditional on the high-skilled labor share, does a region with more apprentices have a higher threshold given globally available technology. Thus, equations (2.15)-(2.17), can be rewritten as,

$$\frac{d\left(\frac{\partial \Delta \ln(Y_t)}{\partial J_t} \frac{dJ_t}{d\ln(N_t)}\right)}{d\lambda} = \frac{d\Delta(\ln(Y_t) - \ln(Y_0))}{d\lambda}\Big|_{L_{RT,0},H_0}.$$

While the regressions showing the differential effect of apprentice and other low-skilled labor across regions, are

$$\Delta \ln(Y_{t,j}) = \beta_0 + \beta_1 L^A_{RT,0,j} + \gamma_1 L^O_{RT,0,j} + H_{0,j} + \epsilon_j, \tag{2.19}$$

where "A" denotes apprentice- and "O" other low-skilled labor in routine tasks and $H_{0,j}$ denotes the region's initial high-skilled share.[17]

Testable Implications

Hypothesis 1. *Conditional on the high-skilled labor share, regions with an apprentice-intensive industry structure adopted fewer computers over time (see equation 2.15).*

Hypothesis 2. *Apprentice-intensive regions, conditional on the high-skilled labor share, have less displacement of routine-labor as new ICT technology is invented (equation 2.16).*

[17]Unlike the theory, regions do not perfectly sort into apprentice- versus non-apprentice regions. Regions have different mix of the two types of education systems, therefore, making it necessary to differentiate between apprentice and other low-skilled labor.

Hypothesis 3. *Apprentice-rich regions should experience a smaller rise in low-skilled services over time, conditional on the high-skilled labor share (equation 2.17).*

To summarize, Figure 2.3 visualizes the effect of hypotheses 1 and 2 or regression equation (2.19). Hypothesis 3 is just the inverse of hypothesis 2.

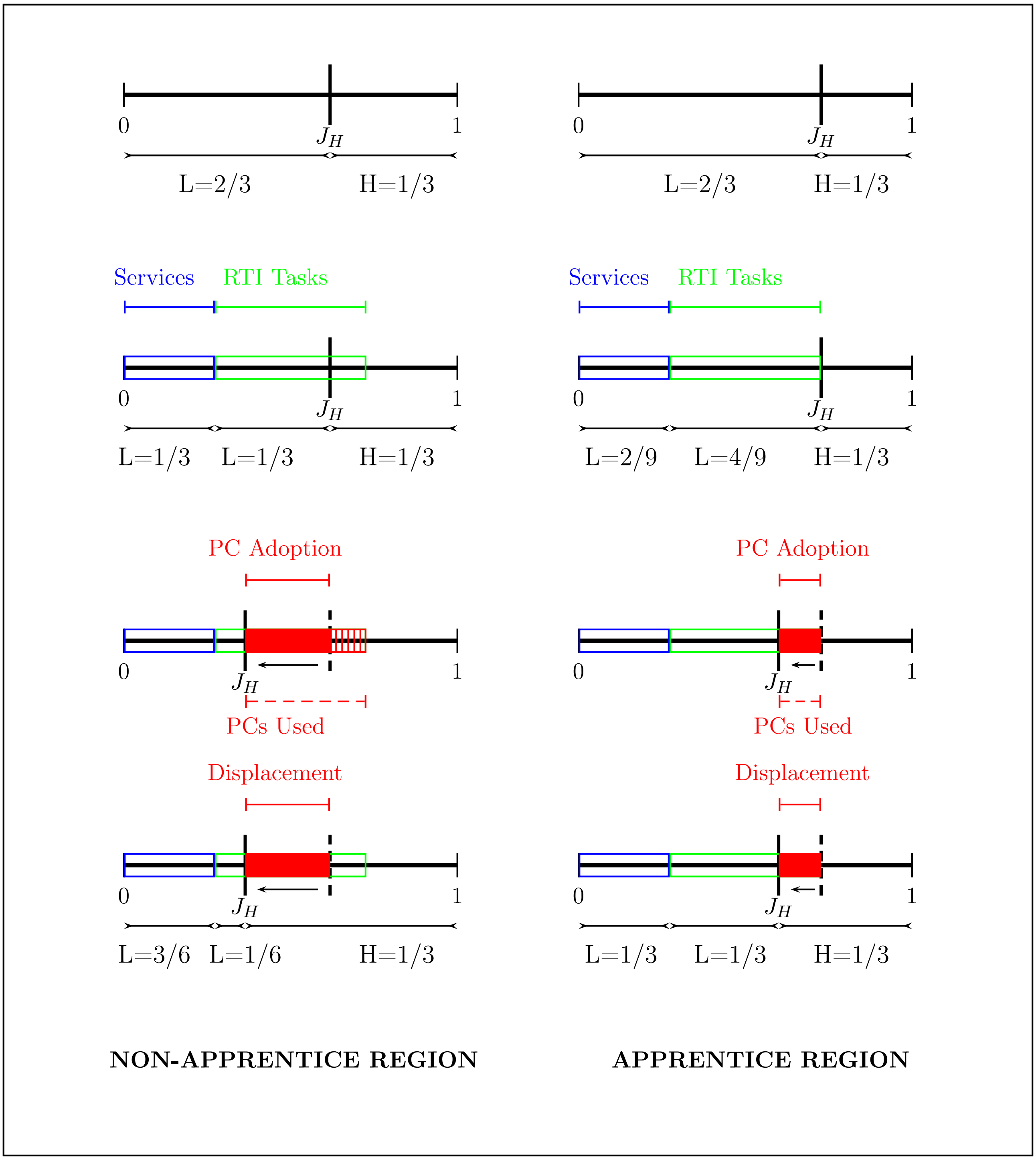


Figure 2.3: **Hypotheses 1 and 2**
The Figure displays the change in the occupational structure across regions upon an increase in ICT capital efficiency. The LHS displays the effect for a non-apprentice region and the RHS panel depicts it for an apprentice-intensive region.

2.3 German Regional Data

This Section summarizes our construction of key variables and data sources. Further detail is provided in Appendix B.2.

2.3.1 Data Sources

Two main data sources are used in this paper: (1) the Sample of Integrated Labour Market Biographies - Regional File 1975-2008 (SIAB-R 7508) (SIAB in the following); and (2) the BIBB/IAB Qualification and Career Survey 1979 and 1999 (QCS in the following). The SIAB sample provides detailed individual-level characteristics, such as education, region of work, nationality, and labor market experience (e.g., occupational status and wages) (see Dorner *et al.*, 2011, for details). The sample used consists of all workers subject to social security payments, aged 17 to 62.[18] If an individual has more than one employer, only the primary occupation is considered. Following Dustmann *et al.* (2009) all workers are weighted by part-time or full-time work given limited information on hours worked in the regional sample.

The QCS is primarily used to construct occupation specific computer usage. In addition, we use task measures computed by Autor and Dorn (2013) for the US to compute task-intensity across the German working population in the SIAB sample. We do so in order to make the research comparable to US studies, even though the QCS also provides information on tasks performed by each individual. Although there are questions in the German data that identify routine, manual, and abstract tasks, these questions are not identical to the US survey and, therefore, will not necessarily capture the same information. Nonetheless, the German task measure provides very similar results. A comparison between the German and US task measures, when applied to the SIAB sample, is provided below.

To compute regional variation, we rely on a similar concept, as in Autor and Dorn (2013), of local labor markets (or commuting zones). To define the German local labor markets, we use the official classification of the "Bundesinstitut fuer Bau-, Stadt- und Raumforschung", which are quasi identical to the classification of the "Gemeinschaftsaufgabe *Verbesserung der regionalen Wirtschaftsstruktur*" (Koller and Schwengler, 2000). Since these zones are based on economic geography by taking into account commuter flows and commuting time, they are a good representation of local labor markets (see Eckey, 1988; Eckey and Klemmer, 1991). Due to limited information in the SIAB dataset, some

[18]This means that civil servants, the self-employed, active-military and students are not included.

regions are aggregated to a broader level. Analysis is restricted to West Germany and contains 182 commuting zones.

2.3.2 Apprentices

Apprenticeship rates in Germany are high and largely stable over time. The vocational education report (*Berufsbildungsbericht*) from 1977 and 2011 (BiBB, 1977; BiBB, 2011), document 496,000 new apprenticeship contracts in 1976, or about 67% of all secondary graduates choose an apprenticeship, and 468,410 new contracts in West Germany in 2010, or about 65% in 2009. According to the reports, roughly 60 percent of apprenticeships are in industry and 25 percent are in artisanry.[19] Of all apprenticeships in 2010, 93 percent were financed by firms and the rest by public funds.[20]

However, while initial apprenticeship numbers are large, a considerable fraction eventually switch industries and occupations, making most of the specific knowledge obsolete. BiBB (1977) states that about 40 percent of male employees that had done an apprenticeship between 1955-1970 switched their broad sector of work. About half of them document that their specific skills became obsolete. Using the QCS sample, we find about 50 percent of apprentices switching industry and about 31 percent switching the broad sector, i.e., services to non-services or vice versa. In the empirical analysis, we only label workers as apprentices if they, at some point, completed an apprenticeship in the same broad sector they are currently employed in. E.g. a worker who finished an apprenticeship in manufacturing, but now works as a service worker, is not labeled an apprentice. This is consistent with the model's assumption that apprentices only have additional productivity in the RT sector.

2.3.3 Measuring Tasks

To make the study comparable to equivalent US studies, we use the task measures computed by Autor *et al.* (2003) across occupations merged to the SIAB sample. We make use of both of the individual tasks as well as the routine measure computed as,

$$R_j = \frac{routine_j}{routine_j + manual_j + abstract_j},$$

for occupation j. Routine tasks are an average of routine-cognitive and routine-manual tasks. Abstract tasks are the average of non-routine personal and non-routine analytical.

[19] Apprenticeships in the reports are classified by occupation.

[20] The portion financed by firms is slightly higher, 95 percent, when restricting the sample to West Germany.

Manual tasks is simple the non-routine manual tasks (for details see Autor *et al.*, 2003). As in Autor and Dorn (2013), an occupation is labeled routine-task-intensive, RTI_j, if the occupation falls within the top one-third of the employment distribution in terms of the R_j measure,

$$RTI_j = \mathbf{1}\left[R_j \geq R^{P66}\right].$$

These occupations are called RTI-occupations. For the analysis of machine adoption we also compute the 66th percentile index for the separate task measures (manual, routine and abstract).

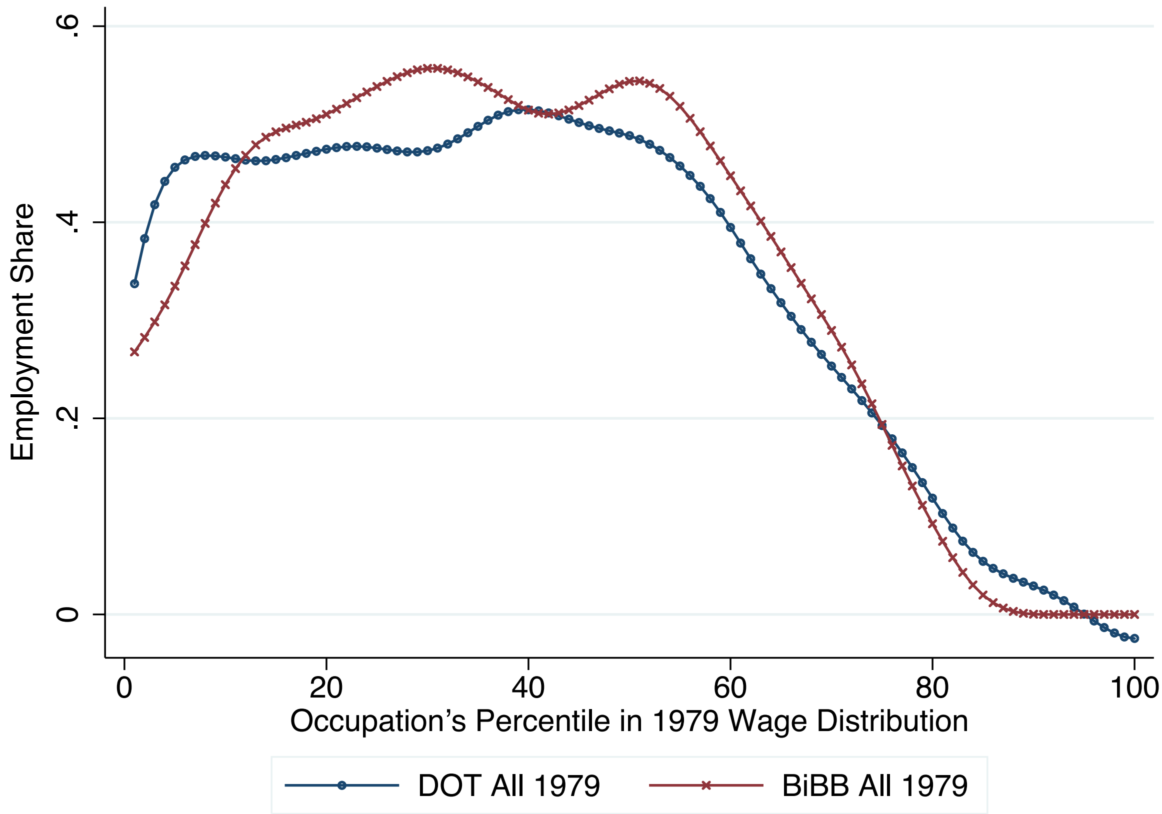


Figure 2.4: **Share of RTI Occupations (DOT vs BiBB) in 1979**

While using US task measures on German occupations might have limitations, we are able to compare the measure to similar German measures. The QCS in Germany, as the dictionary of occupational title (DOT) in the US, provides information on types of tasks done by workers. While the questions asked are not identical between the two surveys, the two measures provide very similar aggregate results. Figure 2.4 shows the share of employment within RTI-occupations for both the DOT and the BiBB measures across the 1980's wage distribution. Given these similarities the results are provided using the US data, since this allows for a direct comparison between this study and US studies.

Similar to Figure 4 in Autor and Dorn (2013), most of the employment in RTI-occupations is in the middle of the wage distribution which falls toward the lower and upper tails. However, unlike the US, the polarization as seen in Figure 2.1 takes place at a higher percentile of the wage distribution. In Germany, most polarization has happened around the 40th and 60th percentile. In the US, most polarization has been around the 20th to 50th percentile. Routine jobs in the US are also consistently at a lower wage percentile rank than in Germany.

It is important to establish that both apprentices and non-apprentices could potentially be replaced by ICT technology. If apprentices were to perform very different tasks (i.e., tasks that are not routine in nature), it might not be surprising that apprentices are not displaced by ICT. As a consequence, Figure 2.2 would simply be a product of apprentices being irreplaceable and not that acquired skills increase their relative productivity. Figure 2.5 graphs the share of routine employment from Figure 2.4 separately, by apprentices versus other workers. More precisely, the left panel (Figure 2.5a) graphs the aggregate RTI measure in employment shares and the right panel (Figure 2.5b) graphs the 66th percentile employment share of occupation that are routine (individual task measure).

(a) RTI (b) Routine

Figure 2.5: **Share of Routine Occupations (Apprentices vs Others) in 1979**

Although apprentices perform less RTI tasks along the lower part of the wage distribution, the overall employment in RTI tasks is similar. Comparing only the routine component of RTI suggests that apprentices and other workers engage in virtually the same amount of routine employment, especially in the middle of the wage distribution were the majority of employment polarization has taken place in Germany. The difference in the aggregate RTI measures is driven by some apprentice occupations performing more manual tasks than other workers.

Comparing the distributions from Figures 2.1, 2.2 and 2.4, 2.5, we propose that - as in the US - German employment polarization is due to the displacement of routine occupations by ICT technology. However, given the evidence of Figure 2.2 and outlined in the theory in Section 2.2, this polarization is slower in apprentice-intensive regions. This occurs even though apprentices work in just as many routine occupations, the "disappearing" occupations, as other low-skilled workers. The next Section formally tests this theory by empirically evaluating the hypotheses as stated in Section 2.2.4.

2.4 Empirical Results

In this Section we separately test our three hypotheses (1) on computer adoption, (2) routine-labor displacement, (3) and service sector growth. As suggested by Figure 2.2 in the introduction, the main prediction is that local labor markets with more apprentices should see less computer adoption, less routine-labor displacement, and lower service sector growth.

To do this formally, cross-section OLS regressions are estimated. The cross-sectional variation comes from the regional differences at the commuting zone level within Germany. As such, all variables are constructed on a regional labor market level. For example, the regional measure of routine-task-intensity, RTI, is defined as the share of employment within region j that works in RTI-occupations k,

$$RTI_{jt} = \left(\sum_{k=1}^{K} L_{jkt} \cdot RTI_k \right) \left(\sum_{k=1}^{K} L_{jkt} \right)^{-1}.$$

As suggested in the introduction, regional apprenticeship variation is likely due to the absence of official federal apprenticeship support prior to the mid-1970s. Instead, local governments made all decisions concerning what schooling to provide and how.

2.4.1 Computer Adoption and Skills

To determine the validity of hypothesis 1, we test whether the adoption of personal computers can be explained by the share of RTI-occupations and/or the share of abstract-occupations in a region.[21] The former would suggest ICT is substitutable with the low-skilled (or routine tasks) and the later would suggest ICT is complimentary with high-skilled (or abstract tasks). In general, one would suspect both effects to be present.

[21]Note that the share of manual-, routine-, and abstract employment within a region does not necessarily add up to one.

Furthermore, the model suggests that regions with more apprentices should see less of substitutability of routine tasks (see equation 2.15).

The computer measure is tabulated from the 1999 QCS. We adopt the standard procedure of assuming that the share of computers in 1999 also captures the growth in computer utilization since 1979. I.e., computers were virtually absent in 1979.[22] The QCS allows us to compute computer adoption by occupations, and the SIAB provides the regional variation in occupational structure. That is, it is assumed that a given occupation adopts computers in a similar way, regardless of location. E.g., it does not matter whether the adoption is located in the South or the North of Germany.[23] For additional detail on the construction of the computer measure see Appendix B.2.2.1.

First, without differentiating between apprentices and others, we regress the computer (PC) measure in 1999, $PC_{j,99}$, on the regional measure of routine-task-intensity, $RTI_{j,79}$,

$$PC_{j,99} = \beta_0 + \beta_1 RTI_{j,79} + \psi_f + \epsilon_j.$$

This regression is directly derived from equation (2.9) in Section 2.2 and the expected sign points to a positive coefficient on $RTI_{j,79}$, $\beta_1 > 0$. Each regression has controls for federal state fixed effects, ψ_f. Standard errors are clustered on the federal state level and all regressions are weighted by each periods' initial employment shares.

Alternatively, we also show the correlation decomposed by separate tasks,

$$PC_{j,99} = \beta_0 + \beta_1 Routine_{j,79} + \beta_2 Abstract_{j,79} + \beta_3 Manual_{j,79} + \psi_f + \epsilon_j.$$

In this specification, the coefficient on routine-labor should still be positive, $\beta_1 > 0$. In addition, the coefficient on abstract-labor should also be positive, $\beta_2 > 0$ and if the complementarity effect is stronger than the substitution effect, the latter coefficient should be greater, $\beta_2 > \beta_1$. Since manual-labor is not easily replaced by computers, and also has little complementarity with computers, we expect the coefficient to be zero, $\beta_3 = 0$.

Table 2.1 shows the correlation between PC Adoption in 1999 and initial employment shares in routine-intensive jobs in 1979 across regions j. Column (1) uses the compounded RTI measure, column (2) uses the individual routine measure, and column (3) uses the three separate measures to distinguish between substitution and complementarity effects. Column (1) and (2) suggest, counter to the theory, that more RTI- or routine employment is associated with less computer adoption. However, the results of column (3),

[22] Although the 1979 QCS does provide computer utilization information, we do not rely on this data since the survey design changed substantially since 1979. Defining computer adoption in 1999 as the change between computer utilization in 1999-1979 would however provide similar results.

[23] Unfortunately, regional variation in the QCS is sparse, and does not allow for a robust measure on the regional level.

Table 2.1: **PC Adoption and Tasks**

VARIABLES	(1) PC_99	(2) PC_99	(3) PC_99
RTI	-0.660***		
	(0.103)		
Routine		-0.663***	0.143**
		(0.0682)	(0.0430)
Abstract			1.133***
			(0.0377)
Manual			0.0176
			(0.0619)
N	182	182	182
R^2	0.530	0.632	0.818

Notes: Standard errors are clustered at the federal state level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include federal state fixed effects (11 federal states). All models are weighted by each periods' initial employment shares. PC adoption is measured in 1999, the independent variables in 1979.

when including all task measures, suggest that both the substitution-of-routine-skills and complementary-to-abstract-skills are present in Germany. The substitution effect is considerably smaller. A region with 10 percentage points more routine employment in 1979 has 1.4 percentage points more computer adoption, whereas 10 percentage points more abstract employment in 1979 results in 11.3 percentage points more computers in 1999. Finally, there is no effect of the manual component.

Having established the same overall effects in Germany as in the US, Table 2.2 explores the differential effect between apprentices and other workers. In doing so, we differentiate the share of workers in RTI-occupations, for example, into apprentice-intensive, $ARTI$ and other occupations, $ORTI$,

$$
\begin{aligned}
ARTI_{j,t} &= \left(\sum_{k=1}^{K} L_{j,kt} RTI_k \times \mathbf{1}\left[APP_k > APP^{P66}\right]\right)\left(\sum_{k=1}^{K} L_{j,kt}\right)^{-1}, \\
ORTI_{j,t} &= \left(\sum_{k=1}^{K} L_{jkt} RTI_k \times \mathbf{1}\left[APP_k \leqslant APP^{P66}\right]\right)\left(\sum_{k=1}^{K} L_{j,kt}\right)^{-1}, \\
&\Rightarrow \quad ARTI_{j,t} + ORTI_{j,t} = RTI_{j,t},
\end{aligned}
$$

where APP_k indicates if the job is apprentice-intensive and thus has an apprentice-share above the 66th percentile. The apprentice-routine, -manual or -abstract and other-routine, -manual or -abstract measures are formed analogously.

Within Germany we see a much larger complementarity effect, and the RTI-measure is unable to pick up the effect in the aggregate. Thus, the next results only focus on the decomposed task measures. Moreover, this allows for a direct comparison of the importance in substitution and complementarity effects. Now the computer (PC) measure in 1999, $PC_{j,99}$, is regressed on the $Routine_{j,79}$, the $Abstract_{j,79}$, and the $Manual_{j,79}$ employment shares, and a control for the high-skilled labor share, $H_{j,t}$:

$$\begin{aligned} PC_{j,99} &= \beta_0 + \beta_1 ARoutine_{j,79} + \beta_2 AAbstract_{j,79} + \\ &\quad \gamma_1 ORoutine_{j,79} + \gamma_2 OAbstract_{j,79} + \delta Manual_{j,79} + \psi_f + \epsilon_j. \end{aligned}$$

Even though equation (2.15) is only conditional on the high-skilled share the control is omitted here, as the correlation between "Abstract" and the high-skilled share is 0.926. Equation (2.15) suggests the coefficient on routine-labor should be smaller in the apprentice region, $0 < \beta_1 < \gamma_1$. Given equation (2.9) it is unclear what the relationship of coefficients on abstract labor, β_2 and γ_2 should be. The model however suggests that these effects would be similar across regions since high-skilled labor is equally productive everywhere.[24]

The results in Table 2.2 are provided both by differentiating all task measures by apprentices and other worker (columns (1)), and only focusing on the routine difference (column (2)). Column (1) sheds light on the purpose of computer adoption across

Table 2.2: **PC Adoption, Apprentices and Tasks**

VARIABLES	(1) PC_99	(2) PC_99
ARoutine	0.0044	0.016
	(0.234)	(0.236)
ORoutine	0.153**	0.154**
	(0.064)	(0.0537)
AAbstract	0.858***	
	(0.160)	
OAbstract	1.585***	
	(0.268)	
Abstract		1.150***
		(0.056)
Manual	0.023	0.046
	(0.067)	(0.098)
N	182	182
R^2	0.835	0.819

Notes: Standard errors are clustered at the federal state level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include federal state fixed effects (11 federal states). All models are weighted by each periods' initial employment shares. PC adoption is measured in 1999, the independent variables in 1979.

[24]The regression does not differentiate between apprentice and other manual employment, since the employment share has no significant effect on computer adoption. However, results are robust to differentiating between manual types.

apprentice-intensity. The coefficient on abstract employment is smaller for apprentices than other workers, but the two measures are qualitatively comparable. Moreover, we cannot reject the null hypothesis that they are statistically equal at the 5 percent confidence level ($F(1,8) = 3.49$). The coefficient on manual employment is insignificant (they are still insignificant if estimated separately). Finally, as more routine jobs are done by other workers, the more computer adoption is observed. Instead, when apprentices work in routine tasks, there is no correlation with computer adoption. Since apprentices work mostly in the middle of the wage distribution, and we cannot reject the null hypothesis that there is a difference in abstract employment, column (2) differentiates only the routine tasks by apprentices. The effect remains qualitatively and quantitatively unchanged. In magnitudes, regions with a 10 percentage points larger routine labor share adopt 1.5 percentage points more PCs. That is, all the substitution effect from Table 2.1 is driven by other workers, not apprentices. This is precisely the prediction from the model, i.e., that workers without specific skills are more prone to replacement. However, until now we have only showed a correlation between routine-labor and computers and have not established if these workers are replaced or simply use computers at work. The next Section shows that these workers are actually displaced.

2.4.2 Routine Shares and their Displacement

The model suggests that with the invention of ICT technologies, the low-skilled working in routine tasks should be displaced. However, apprentice-intensive regions should have less displacement of routine-labor, since the rate of adoption of new technologies is slower. Visually, Figure 2.6 shows the correlation of apprentice intensity and routine displacement in a similar manner as Figure 2.2b for computers. The negative raw correlation between the share of new apprentice contracts in 1978-1979 and the displacement of RTI-labor shares for the 1979-2008 time period is $-.26$.

First, we establish the general results irrespective of regional apprenticeship rates. The regression of the change in routine task intensity (the employment share in routine-intensive occupations) on the period's initial routine task intensity, is

$$\Delta^{(t+10)-t} RTI_j = \beta_0 + \beta_1 RTI_{j,t} + \psi_f + \theta_t + \epsilon_j, \tag{2.20}$$

which follows from equation (2.10). Given the theoretical framework and the evidence from the US, we expect the coefficient on RTI-labor to be negative, $\beta_1 < 0$. The more routine-labor a region has, prior to technology innovation, the more routine-labor can potentially be displaced by machines.

Again, all regressions have controls for federal state fixed effects and time fixed effects,

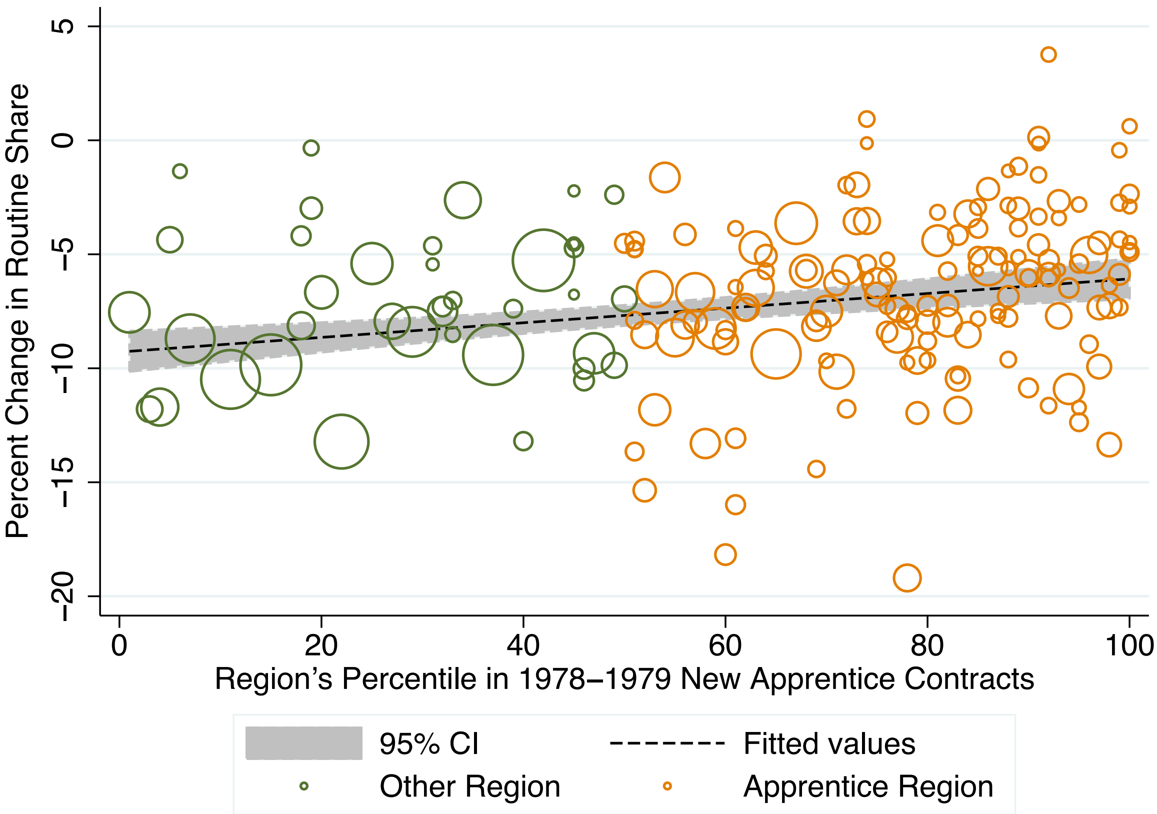


Figure 2.6: **Displacement by Region and 1979 Apprentice Intensity**

θ_t, standard errors are clustered on the federal state level and results are weighted by the period's initial employment shares. For brevity we report results for the compounded measure only, although results for the separate routine measure are comparable.[25] Table 2.3 column (1) is a stacked multi-period model, where the dependent variable is the decade change in the routine share. Again, counter to the theory, the results suggest that the greater the routine-intensive employment share, the less routine-labor displacement. Column (2) repeats column (1), but differentiating by apprentice and other employment. That is, the change in employment is regressed on initial apprentice or other RTI-employment and the initial high-skilled labor share, $H_{t,j}$,

$$\Delta^{(t+10)-t} RTI_j = \beta_0 + \beta_1 ARTI_{j,t} + \gamma_1 ORTI_{j,t} + \delta H_{t,j} + \psi_f + \theta_t + \epsilon_j. \tag{2.21}$$

The control for the high-skilled labor share follows directly from equation (2.16), since apprentice regions show less displacement only conditioning on the high-skilled labor share. Moreover, given the sign from the cross-derivative of equation (2.16), the coefficient on routine-labor should be negative, but in absolute value larger for other employment, i.e., $\gamma_1 < \beta_1 < 0$. Column (2) corroborates the theory, finding displacement for other work-

Table 2.3: **Routine Displacement, Apprentices and Tasks**

VARIABLES	(1) $\Delta^{(t+10)-t}$ RTI	(2) $\Delta^{(t+10)-t}$ RTI	(3) Δ^{89-79} RTI	(4) Δ^{99-89} RTI	(5) Δ^{08-99} RTI
RTI	-0.0710				
	(0.0400)				
ARTI		0.010	-0.003	0.064	0.025
		(0.130)	(0.237)	(0.100)	(0.228)
ORTI		-0.219***	-0.079	-0.406***	-0.207**
		(0.052)	(0.049)	(0.120)	(0.089)
N	546	546	182	182	182
R^2	0.309	0.371	0.152	0.490	0.163

Notes: Standard errors are clustered at the federal state level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include federal state fixed effects (11 federal states). Columns (1)-(2) include time fixed effects (3 decades). Columns (2)-(5) control for the region's initial high-skilled share. All models are weighted by each periods' initial employment shares.

ers, but not apprentices. That is, a region with a 10 percentage points higher routine-labor share faces a 2.19 percentage points faster decrease in its routine labor share (per decade).[26] This is about the same effect that Autor and Dorn (2013) find for the US (see Table 3 in their paper). The authors find a 2.95 percentage points displacement per decade in the US. In contrast, a region with a 10 percentage points larger apprentice

[25]The results are available from the authors upon request.

[26]Using the separate routine measure, gives a slightly smaller, but still comparable, impact of 1.7 percentage points in a decade.

routine-labor share has no effect. These results are robust to a number of additional controls, e.g. the employment share in services, the female employment share, the share of immigrants, the share of youth (age 25 and below), and the share of part-time workers. With these additional controls the coefficient on apprentice routine-labor is always insignificant. The coefficient on other routine-labor varies between -0.331 and -0.221 and is always significant at the 1 percent confidence level.

Column (3) - (5) show results separately for each decade.[27] Splitting the effect by decade shows that most of the replacement took place for other workers between 1989 and 1999. However, the apprentice routine-labor coefficient is insignificant and close to zero during all decades. In fact, the 1990s was the period where ICT adoption exploded. Nordhaus (2007) shows that computer power increased and prices decreased the most between the 1980s and late 1990s. According to the author, improvement in computer technology was most pronounced between 1985-1995.

Alternatively, Table 2.4 shows the effect over a longer time horizon, from 1979 to 1999 and from 1979 to 2008. This long-term perspective is done by regressing the overall change in routine employment shares between $t = 0$ and $t = T$ on the initial routine intensity in 1979. Column (2) and (4) include controls for the high-skilled labor share.

Table 2.4: **Routine Displacement, Apprentices and Tasks in the Long-run**

VARIABLES	(1) Δ^{99-79} RTI	(2) Δ^{99-79} RTI	(3) Δ^{08-79} RTI	(4) Δ^{08-79} RTI
RTI	-0.182*		-0.124*	
	(0.0921)		(0.0652)	
ARTI		0.036		0.023
		(0.209)		(0.204)
ORTI		-0.472**		-0.448***
		(0.142)		(0.046)
N	182	182	182	182
R^2	0.318	0.484	0.342	0.535

Notes: Standard errors are clustered at the federal state level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include federal state fixed effects (11 federal states). Columns (2)-(4) control for the region's initial high-skilled share in 1979. All models are weighted by each periods' initial employment shares.

In the long-run, aggregate effects are negative and significant at the 10 percent level. In terms of magnitude, the coefficient for the first twenty years suggests that a region with a 10 percentage points higher routine labor share has a 0.9 percentage points lower routine-labor share within 10 years, and an 1.8 percentage point decrease after 20 years. Over the entire 29 years, the result is slightly smaller but still similar. The results for column

[27] To make results comparable across decades, column (5) is adjusted for the missing years. I.e., all results in Table 2.3 can be interpreted as 10-year changes.

(2) and (4) are identical to above, there is no effect for apprentice routine-labor and an effect similar to the US for other routine-labor. Comparing the results from Table 2.4 and Figure 2.6 suggest that the displacement results are robust to different specifications.

2.4.3 Routine Shares and Service Employment

Having determined the displacement of routine-labor, we need to establish whether this displacement comes with a rise in services. More precisely, low-skilled service jobs could possibly replace routine-labor as in the US.

Tables 2.5 and 2.6 regress the change in the low-skilled service sector share and the service sector share on the same set of variables as above. The results are presented in decades, similar to regressions (2.20) and (2.21). Given the cross derivative, equation (2.17), the only difference is that we expect the coefficients to have the opposite sign.

The low-skill service sector is defined as the share of regional employment that works in certain service occupations. Following the definition of Blossfeld (1985), low-skilled service occupations range from "hairdresser" and "street and indoor cleaners" to "attending on guests" and "nursing assistants".

Table 2.5: **Low-Skilled Services, Apprentices and Tasks**

	(1)	(2)	(3)	(4)	(5)
VARIABLES	$\Delta^{(t+10)-t}$ LS	$\Delta^{(t+10)-t}$ LS	$\Delta^{(t+10)-t}$ LS	Δ^{99-79} LS	Δ^{08-79} LS
RTI	0.023**				
	(0.009)				
ARTI		-0.014	-0.008	-0.074	-0.178
		(0.0213)	(0.069)	(0.093)	(0.159)
ORTI		0.024	0.028**	0.072***	0.111***
		(0.021)	(0.012)	(0.020)	(0.032)
N	546	546	546	182	182
R^2	0.499	0.499	0.499	0.209	0.214

Notes: Standard errors are clustered at the federal state level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include federal state fixed effects (11 federal states). Columns (1)-(3) include time fixed effects (3 decades). Column (2) controls for the region's initial high-skilled share. All models are weighted by each periods' initial employment shares. The regional low-skill service share (dependent variable) is defined as the employment share working in low-service occupations defined after Blossfeld (1985).

The results in column (1) suggest that more routine-labor and larger growth in low-skilled services are related. In magnitude this is about one-third of the effect in the US. Given the lack of polarization at the lower end of the wage distribution in Germany (see Figure 2.1) it is not surprising that the results for the share of low-skilled services are smaller in magnitude (see Table 2.5). Column (2) controls for the high-skilled labor share and splits the results by apprentices versus other routine-labor. Both results are insignificant when controlling for the high-skilled labor share. However, consistent with the theory, the effect on other routine-labor is larger and positive (and almost significant). As it turns out, not controlling for the high-skilled share, column (3), preserves the same results, but now the coefficient on other routine-labor is significant at the 5 percent level. This result is consistent with, for example, the theory postulated by Manning (2004) and Mazzolari and Ragusa (2013), who suggest that high-skilled labor demands low-skilled services. Thus, the more high-skilled labor the higher the demand for low-skilled services. The last two columns, (4) and (5), show the long-run trends. The results are similar in magnitude for the entire time period. Having a 10 percentage points larger (other) routine labor share in 1979 leads to a growth in low-skilled services of 1.1 percentage points over the entire period, compared to a 1.1 percentage point increase over one decade in low-skilled services for the US (see Autor and Dorn, 2013, Table 5). The results are in line with the previous results (see Tables 2.3 and 2.4) as the aggregate effect is solely driven by other workers, not apprentices.

However, the rise in low-skilled service employment in Germany is relatively small. Although the theory is such that labor is always pushed to the lower-end of tasks, it could be that some low-skilled labor who acquired specific-skills are more likely to move to abstract tasks. Table 2.6 repeats the analysis from Table 2.5 for the entire service sector.[28] Column (2) through (4) use the high-skilled labor share as a control. Column(1)

Table 2.6: **Services, Apprentices and Tasks**

VARIABLES	(1) $\Delta^{(t+10)-t}$ S	(2) $\Delta^{(t+10)-t}$ S	(3) Δ^{99-79} S	(4) Δ^{08-79} S
RTI	0.008			
	(0.037)			
ARTI		-0.269	-0.691	-0.795
		(0.232)	(0.566)	(0.540)
ORTI		0.161***	0.461***	0.452***
		(0.036)	(0.092)	(0.047)
N	546	546	182	182
R^2	0.473	0.503	0.376	0.420

Notes: Standard errors are clustered at the federal state level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include federal state fixed effects (11 federal states). Columns (1)-(2) include time fixed effects (3 decades). Columns (2)-(4) controls for the region's initial high-skilled share. All models are weighted by each periods' initial employment shares. The regional service share (dependent variable) is defined as the employment share working in the service sector.

shows that there is no aggregate effect on the service sector size. But again, when splitting routine-labor by apprentices and other workers, the results suggest that regions high in routine-labor not performed by apprentices in 1980 saw service sector growth. The

[28]Non-services are defined as agriculture, construction, mining and manufacturing. Services are then wholesale & retail trade, personal & business services, transport, education, health, public administration and cleaning services.

coefficient on apprentice labor is insignificant, but the coefficient on other routine-labor is significant and large, similar to US estimates for the low-skilled service sector. Since apprentices mostly work in industry and are not displaced similarly to other workers, regions with many apprentices should see a slower rise in the service sector. Furthermore, much of the change happens in the 1990s, aligning with the displacement effects.

2.4.4 Wage Polarization

Unlike the US (see Figure 1 panel B in Autor and Dorn, 2013), Germany has seen little *wage* polarization in terms of wage growth along the skill distribution (see Figure 2.7). Consistent with the complementarity of ICT technologies and high-skilled labor, the top

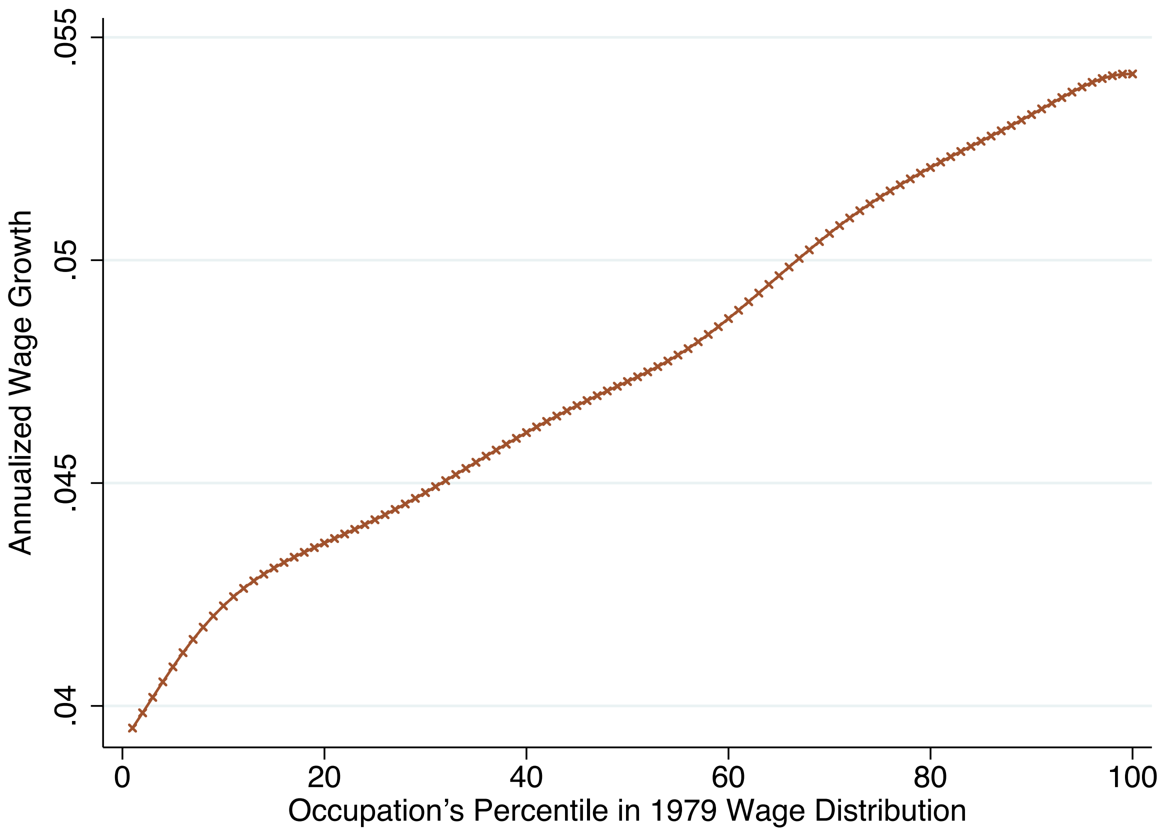


Figure 2.7: **Wage Growth and 1979 Wage Distribution**

of the skill distribution has had the highest wage growth. Dustmann *et al.* (2009) find a rise in the wage differential of middle-skilled (apprenticeship holders) relative to the low-skilled starting in the 1980s. However, they find no clear trend between the high- and middle-skilled.

In addition, the literature has found little wage polarization in Germany, but rather wage dispersion (consistent with employment polarization). The conclusion is that wage adjustments have been avoided due to institutional policies, e.g. centralized wage bargaining and generous unemployment benefits (see Dustmann *et al.*, 2009; Kohn, 2006; Antonczyk *et al.*, 2010; Senftleben and Wielandt, 2012). Given the limited evidence in our data sample, and that an analysis of wage polarization would have to take into account different regional institutional factors, it is outside the scope of this study to further investigate these trends.

2.5 Conclusion

ICT technology adoption has led to substantial employment polarization across the world. The standard theory suggests that routine tasks performed by the middle-skilled are most prone to displacement by computers. However, when quantifying the investment in computer adoption over the last couple of decades across German regions, the data suggests that regions with the least routine employment have the most computer adoption. This apparent puzzle - which stands in sharp contrast to the US - is resolved by studying more closely the composition of non-college labor in Germany. That is, in this paper, we develop a stylized one-sector model that demonstrates the importance of the educational-system, general versus specific training, in incentivizing firms to adopt skill-replacing technologies. Since firms that train apprentices, invest resources in doing so, the adoption of ICT technologies that replace non-college labor is more costly. As, due to their specific training, apprentices are more productive than other middle-skilled labor. Consequently, regions with a large number of apprentices, see less ICT adoption (here in terms of computers, given data availability), but also less displacement of routine-labor and less employment polarization.

For the empirical analysis we make use of regional variation in apprentice intensity across German local labor markets prior to the 1980s. The empirical results show virtually no displacement of apprentice routine-labor, while for other (non-apprentice) routine-labor the effects are similar in magnitude, in terms of labor displacement, to the US results. That is, a region with a 10 percentage points higher routine-labor share has a 2.19 percentage points faster displacement of routine-labor per decade. The results on computer adoption and service employment are in the same direction as in the US, but magnitudes are smaller.

3 Directed Technical Change, The Environment and The Role of Emerging Markets

3.1 Motivation

Although industrialized countries started to impose environmental regulations, CO2 emissions are rising on a global scale. This fact is triggered by the emerging countries that lack environmental regulations and - through their rapid economic growth - account for an increasing fraction of global CO2 emissions. Figure 3.1 displays the aggregate CO2 emissions within China and the US. The linear fit (dashed line) suggests that Chinese emissions rose by about 5.6% p.a., overtaking the US as the largest CO2 emitter in 2005. And even if per capita emissions are still lower in emerging markets, they are projected to increase continuously.[1] The source of these alarming figures is found in missing environmental regulations and a government that is only concerned about maximizing economic growth. Fang *et al.* (2009) document the "develop first, clean up later" strategy of China that served the industrialized countries, but is no longer sustainable in a world of rising total emissions. In fact, emerging markets face an environmental challenge that is three-fold: first, emissions rise as population and production increases. According to the International Energy Agency (IEA), Non-OECD countries will account for 90% of world population growth and 70% of global economic growth. Second and closely related, energy demand increases. The IEA forecasts that 90% of total energy demand growth between 2010 - 2035 will be attributed to emerging markets. Finally, relying on coal as their main energy source, emerging markets face an increasing carbon intensity of energy production. Their carbon intensity of energy use between 1971 - 2009 increased on average by 1.1% p.a. (China) and 2.1% p.a. (India) while industrialized countries (e.g. US, EU) managed to decrease theirs by about 0.5% p.a.[2] And at the same time as Non-OECD countries account for a major share of global emissions and economic growth, they start moving from an "imitation strategy", to building up own innovation facilities.
These facts raise three questions: first, are unilateral policies sufficient to prevent a global environmental disaster? Second, will emerging markets become innovators instead of

[1]Figure C.1 in Appendix C.2 compares the evolution of per capita emissions across countries.

[2]Figures taken from the Worldbank database. See the bibliography for further detail.

imitators? Third, what are the economic consequences for countries subject to binding regulations in terms of long-run growth, international competitiveness and economic welfare?

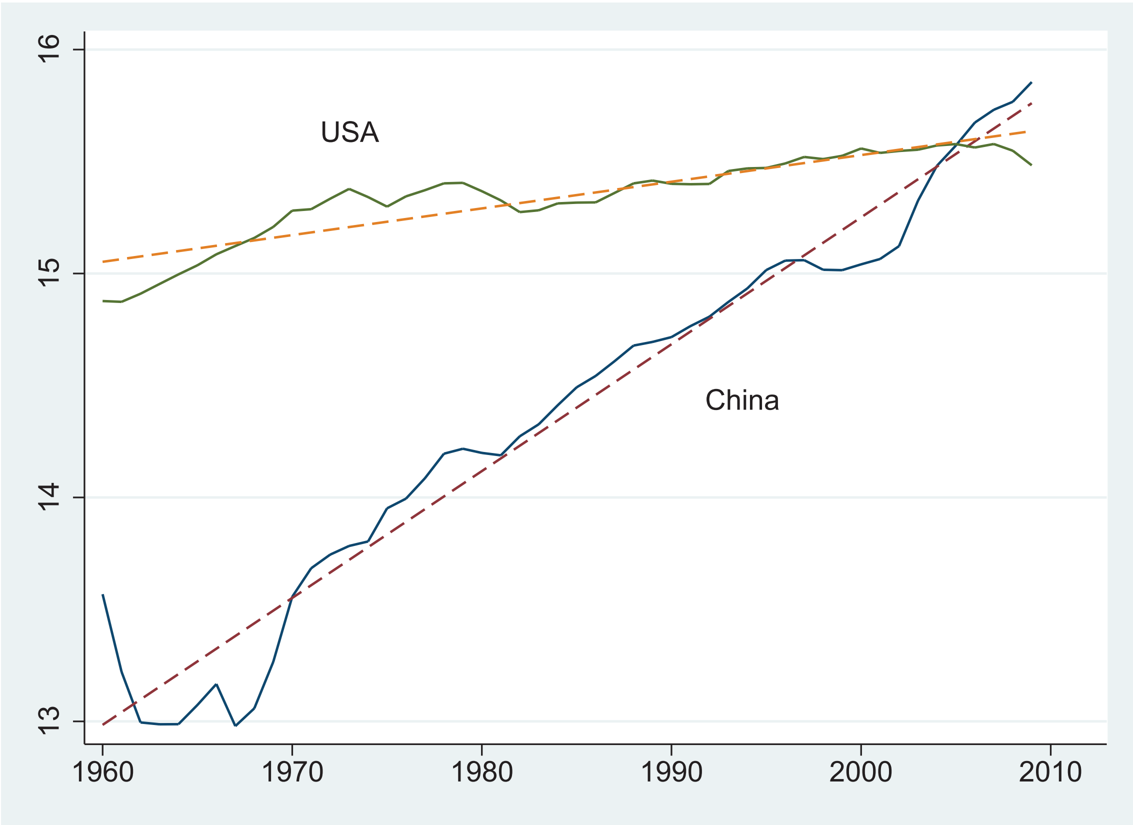


Figure 3.1: Aggregate CO2 emissions (kt)

Notes: The figure displays the evolution of log-linearised aggregate CO2 emissions (in kt) for China and the US. The dashed line represents a linear fit for Chinese and US data. The slope coefficients for China and the US are given by 0.056 (st. error 0.002) and 0.012 (st. error 0.001). Source: worldbank.org (database).

This paper tries to answer these questions in a directed technical change model, where entrepreneurs invest either in "dirty" or "clean" production techniques. By extending the model into a global perspective and introducing a negative pollution externality, I analyze the interaction between unilateral environmental regulations and the direction of R&D investments that are shaped endogenously.[3] As the technologically leading North imposes environmental regulations, the paper studies the optimal behavior of entrepreneurs within the unregulated South. The key decision for entrepreneurs is either to invest in polluting or in "clean" technologies. Depending on the initial distance to the technological frontier of the South and the relation between countries' growth rates, I find three possible long-run outcomes: first, if clean technologies are growing fast within the regulated country, the unregulated South also finds it optimal to invest in clean technologies. However, at the same time there exists the risk of a "dirty production trap" where the South specializes in the "dirty" sector and either continues imitating Northern technologies or starts innovation.

In doing so, this paper relates to the growing literature on the interaction between growth and the environment. While early strands of the literature, among others e.g. Gradus and Smulders (1993) and Stokey (1998), emphasize the trade-off between higher growth and a "healthier" environment, this paper, in contrast, explicitly takes into account the response of technological progress itself. This effect substantially reduces the barriers to switch away from polluting technologies to a sustainable growth path. Empirical evidence for the induced innovation channel comes from Newell *et al.* (1999) and Popp (2002), who exploit the evolution of energy prices and the direction of research. Allowing for the development of non-polluting "backstop" technologies releases the tension between higher growth and less pollution. This idea is explored further by Acemoglu, Aghion, Burstzyn and Hemous (2012) (AABH henceforth), who show that in the absence of regulations, all research investments are channelled towards the dirty sector. In a one-country setup representing the developed world, they characterize the optimal policy that prevents such a disaster as a combination of a carbon tax and research subsidies to the clean sector.
Extending the analysis into a global framework, most literature has recognized the "pollution haven effect" as polluting industrial activities tend to shift from regulated to unregulated countries. DiMaria and Smulders (2004) analyze the interaction between different environmental regulations, trade and pollution. Through the channel of technology diffusion the less regulated South adopts (partially) clean technologies from the regulated North such that whenever this effect dominates the "pollution haven effect" of free trade,

[3] Compare Acemoglu (1998) and Acemoglu (2002) for the idea of directed technical change.

unilateral policies are enough to prevent a global environmental disaster. On the other hand, Hemous (2012) considers the case where both countries are innovators of new technologies.[4] Extending the framework of AABH (2012) to a second country, his paper focuses on the role of international trade between countries with different environmental regulations. In contrast to this work, my model abstracts from international trade but allows countries to either imitate or innovate. Initially the South is the technological follower. However, as the North abandons innovation in the "dirty" sector, the South gets the chance to catch up with the frontier and to overtake the leadership. As in Acemoglu *et al.* (2006) countries that are close enough to the frontier find it optimal to invest in own innovation activities rather than keeping the imitation strategy forever. Now in contrast to Hemous (2012), countries are still linked through the cross-country technology spillovers, which bears interesting implications. Moreover, as growth rates differ between countries (and sectors), the technological frontier can be defined by either the North or the South. Thus, the model allows me to study the path of relative technology stocks, the direction of technical change and its implications on economic welfare in a very rich setting.

The rest of the paper is organized as follows: Section 3.2 documents the increasing innovation activity of emerging markets, in particular China. Section 3.3 introduces the Benchmark Model, that builds upon AABH (2012).[5] Section 3.4 analyzes the optimal behavior of the South under unilateral environmental regulations enforced in the North. Section 3.5 discusses the different possible long-run outcomes and Section 3.6 concludes.

3.2 Innovation Activity

Figure 3.2 plots the increasing innovation capacity of China by measuring the number of patents granted to domestic residents within China. Although the majority of patents is classified as "utility model patents", the number of invention patents is increasing sharply, which indicates that China is moving from an imitation to an innovation strategy. While patents measure innovation output, R&D inputs are increasing accordingly. Over the last 15 years the number of scientists and in particular (governmental) spending into R&D has increased enormously. According to the Worldbank, Chinese R&D expenditures amounted to 1.7% of GDP in 2009, which is more than upper middle income countries spent on average.[6] Although in absolute terms still less than the US or Japan (around 3%

[4]Apart from a brief section, where he considers global knowledge or the case of possible diffusion of technologies.

[5]For further details the reader is referred to their paper.

[6]An "upper middle income" country, according to the Worldbank classification, is defined as a country with a GNI per capita of US $ 4,036 - US $ 12,475 in 2011 calculated using the World Bank Atlas method.

), the R&D expenditures (relative to GDP) in China tripled between 1996 - 2009, rising on average by 8.8% per year. In contrast, within developed countries such as the US or Japan, expenditures grew at a much slower rate of 1.0 - 1.5%. Taking into account the fact that during this interval (1996 - 2009) China's GDP grew at a much higher rate (about 9.8 % p.a.), the increase in R&D expenditure for emerging markets is even more drastic in absolute terms. Finally, Figure 3.3 plots the ratio of patents granted per million US $ of R&D expenditure. Interpreting this ratio as a measure of effectiveness of innovation activities, three facts are remarkable: (i) Chinese efficiency in R&D rose by 5.8% p.a. between 2001 - 2010; (ii) Chinese are more effective in innovating than the US and (iii) by 2009 the Chinese and Japanese innovation activities had converged, such that China has come to compete with one of the most innovative countries of the world.

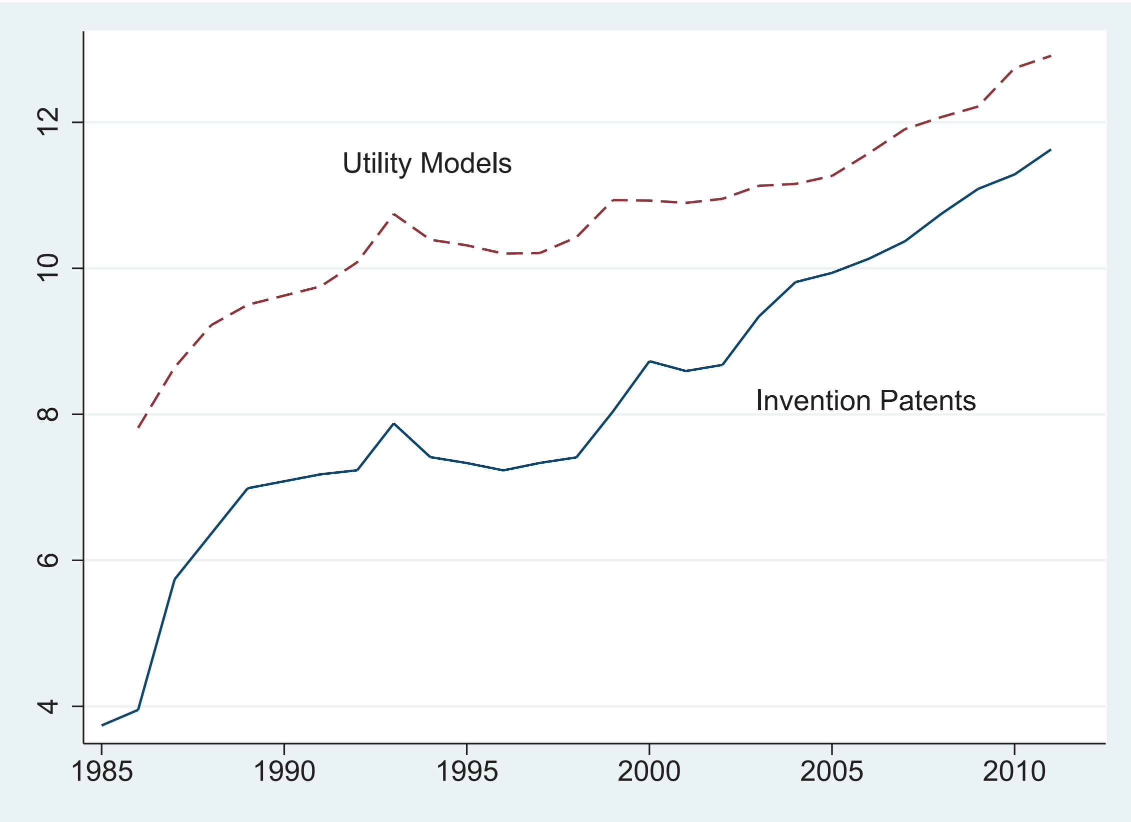


Figure 3.2: Domestic Patents by Chinese Residents

Notes: The figure plots the logarithm of the number of patents obtained by domestic residents within China broken down in invention and utility patents, where the dashed line indicates the utility models.
Source: www.wipo.int - Tables: "Patent grants by patent office, broken down by resident and non-resident (1883-2011)" & "Utility Models granted by patent office, broken down by resident and non-resident (1977-2011)".

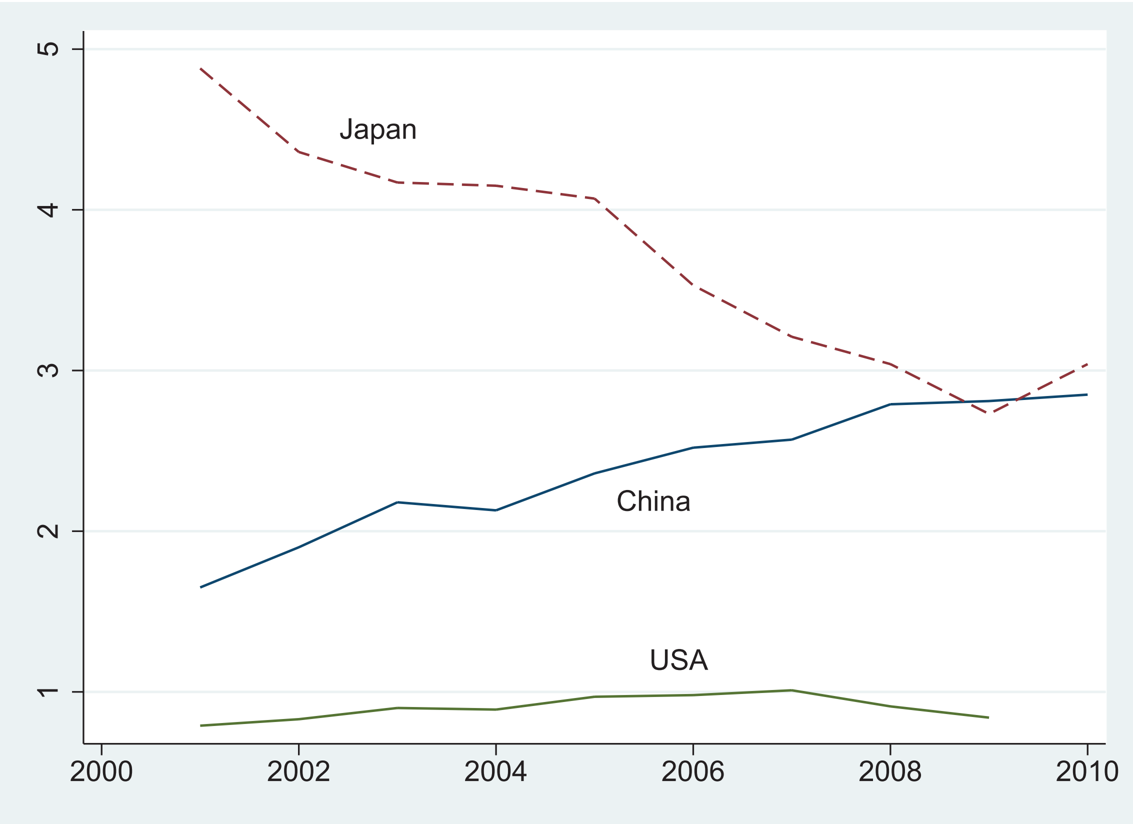


Figure 3.3: Resident Filings per mio. US $ R&D Expenditure

Notes: The figure plots the number of resident patent filings per mio. US $ R&D expenditure (using 2005 PPP weights). Source: www.wipo.int - Table: "Resident patent filings per $ million research & development (R&D) expenditure (2001-2010)".

3.3 The Benchmark Model

The key ingredients are two different types of technologies, that differ with respect to their pollution intensity. "Dirty" technologies that establish the traditionally used technologies can be thought of as production processes that create vast emissions, sewage water and the like. In particular private firms do not internalize this negative externality that is caused as a by-product of production. The alternative production method is called "clean" and resembles modern production technologies like machines using electricity rather than petrol.

In a two-country setup, each country produces a homogenous final consumption good that is made of two intermediates, where one intermediate is produced by dirty production technologies and the other by clean. Thus, the intermediate sectors are labeled as either being clean or dirty. The technological frontier is initially determined by the North, while the South advances through imitation. The paper's focus lies on the question of how unilateral environmental regulations imposed in the North affect profit incentives, and hence the direction and form of technological progress in the South.

3.3.1 The Model Setup

Production and Technology

Within each country $i \in \{N, S\}$ final output Y_t^i is produced using two intermediate inputs, Y_{dt}^i and Y_{ct}^i, where the former represents the aggregate output of the dirty sector and the later is aggregate output of the clean sector

$$Y_t^i = \left[{Y_{dt}^i}^{\frac{\epsilon-1}{\epsilon}} + {Y_{ct}^i}^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}} .$$

Dirty and clean intermediates are imperfect substitutes, where $\epsilon \in (0, \infty)$ governs the elasticity of substitution between them. Whenever $\epsilon > 1$ the goods are gross substitutes and gross complements whenever $\epsilon < 1$. Motivated by the literature and increasing substitution possibilities for dirty inputs, I set $\epsilon > 1$. Countrywide pollution intensity is determined by the relative usage of clean intermediates Y_{ct}/Y_{dt} which itself is governed by the technology ratio.[7]

[7]The fact that some goods are more energy intensive and hence more pollution intensive in its production ex-ante, could be captured by varying values for ϵ. However, this is beyond the scope of the paper.

The production function at the sectoral level $j \in \{d, c\}$ is given by

$$Y_{jt}^{i} = \left(L_{jt}^{i}\right)^{1-\alpha} \int_{0}^{1} \left(A_{jmt}^{i}\right)^{1-\alpha} \left(x_{jmt}^{i}\right)^{\alpha} dm. \tag{3.1}$$

Both sectors $j \in \{d, c\}$ use labor, L_{jt}^{i} and a unit-interval of sector-specific machines, x_{jmt}^{i}, as inputs. A_{jmt}^{i} denotes the quality of machine of type m in sector j at time t. Normalizing the total labor force to 1 within each country, labor market clearing requires

$$L_{ct}^{i} + L_{dt}^{i} \leqslant 1.$$

As standard in the endogenous growth literature, machines are supplied by monopolistically competitive producers. Independent of time, sector or quality, the production of one unit of any machine costs ψ units of the final good. Without loss of generality, I normalize $\psi = \alpha^2$. Technological progress is as follows: at the beginning of each period, each scientist decides whether to direct research towards the dirty or the clean sector. Upon this decision she is then randomly allocated to one machine on the unit interval. Upon successful innovation she obtains a one-period patent and becomes the entrepreneur for production of machine m in this period. Note that not one specific machine but rather the sector is targeted, which leads to entrepreneurs comparing relative profits between sectors (not between specific machines). Denote by s_{jt}^{i} the number of scientists working in sector j at time t and normalize the total to 1. Then market clearing for the scientists implies

$$s_{ct}^{i} + s_{dt}^{i} \leqslant 1.$$

Before specifying the exact form of technological progress within the economy, let me define the sectoral technology level in sector j as the average over all machines m in sector j[8]

$$A_{jt}^{i} = \int_{0}^{1} A_{jmt}^{i} dm. \tag{3.2}$$

Using this, technical progress on the sectoral level is

$$A_{jt}^{i} = \left(1 + s_{jt}^{i}\gamma_{j}^{i}\right) \left(A_{j,t-1}^{i}\right)^{1-\phi-\delta} \left(\bar{A}_{j,t-1}\right)^{\delta} \left(A_{max,t-1}^{i}\right)^{\phi}, \tag{3.3}$$

[8] For simplification, initial productivity is equal for all machines within one sector: $A_{jm,t=0}^{i} = A_{jm',t=0}^{i} = A_{j,t=0}^{i}$.

where for $j \in \{c, d\}$ and $i \in \{N, S\}$,

$$\begin{aligned} \delta > 0 \ if \left\{\forall j : A^i_{j,t-1} \neq \bar{A}_{j,t-1}\right\} \\ \delta = 0 \ if \left\{\exists j : A^i_{j,t-1} = \bar{A}_{j,t-1}\right\}. \end{aligned} \tag{3.4}$$

$\bar{A}_{j,t-1}$ denotes the sector-specific technological frontier and $A^i_{max,t-1}$ denotes the country-specific technological frontier. In general, the state of technology in sector j depends on four components: (i) technological progress features *state dependency* as the size of further innovations increases in the stock of existing technologies within this sector; (ii) it depends on the absolute mass of entrepreneurs investing in technology j (denoted by s^i_{jt}); (iii) ϕ controls the spillover between sectors within the same country and (iv) δ controls the possible spillover from the sector-specific world technological frontier, $\bar{A}_{j,t-1}$. However, if the country is the technological leader within at least one sector, this specific spillover is mute. Interpreting this spillover as foreign FDI investments means that there are no incentives to boost the technology level of a country that is already operating at the world technological frontier.[9]

Pollution and Abatement

Production of the dirty intermediate creates a negative externality on individuals by degrading environmental quality. The flow of pollution is directly proportionate (captured by ξ) to the amount of dirty output, Y_{dt}, but decreasing in the amount of abatement techniques ABT^i_t

$$P^i_t = \frac{\eta Y^i_{dt}}{ABT^i_t}, \tag{3.5}$$

where pollution is bounded from below by some lower bound, such that $P^i_t \in [\underline{P}, \infty)$.[10] As Brock and Taylor (2010) note, the existence of abatement techniques captures the fact that even without any regulations cost-minimizing firms have an incentive to minimize energy inputs and recapture waste products. Abatement activities are not explicity modeled but rather improve at some endogenous rate $(1 + \theta_t)$. This rate is determined by the rate of technical progress within the clean sector weighted by the relative stock of clean

[9]This assumption is made to simplify the transitional dynamics. Abstaining from it leaves the main results unchanged.

[10]An alternative specification would be to define preferences over the stock of pollution, as $P^{Stock}_t = P^i_t + P^{Stock}_{t-1} - \omega P^{Stock}_{t-1}$, where $P^i_t = \frac{\eta Y^i_{dt}}{ABT^i_t}$ denotes the flow of pollution and $\omega \geqslant 0$ is the (possible positive) rate of environmental regeneration.

technologies and thus, can be time-varying[11]

$$
\begin{aligned}
ABT_t^i &= (1+\theta_t^i)ABT_{t-1}^i, \\
(1+\theta_t^i) &= \left(\frac{A_{ct}}{A_{dt}}\right)^i \cdot \left(\frac{A_{ct}}{A_{c,t-1}}\right)^i, \\
ABT_{t=0}^i &= A_{c,0}^i.
\end{aligned}
\tag{3.6}
$$

Finally, the flow of global pollution, P_t, is defined as the aggregate of both countries' flow of pollution

$$
P_t = P_t^N + P_t^S. \tag{3.7}
$$

Observe that the growth rate of global pollution converges to the growth rate of the maximum of local pollution, $\lim_{t\to\infty} \frac{P_t}{P_{t-1}} \to \max\left\{\frac{P_t^N}{P_{t-1}^N}; \frac{P_t^S}{P_{t-1}^S}\right\}$.

Preferences

There is a unit-mass of infinitely-lived households within the economy. A household exists of one entrepreneur and one manufacturing worker. Population is constant over time and labor is supplied inelastically.
The utility function of the representative household of country i is given by

$$
\begin{aligned}
&\sum_{t=1}^{\infty} \beta^t U(C_t^i, P_t), \\
U_t^i &= \log(C_t^i) - B\frac{(P_t)^\chi}{\chi},
\end{aligned}
\tag{3.8}
$$

where $i \in \{N, S\}$, $\chi \geqslant 0$ and β is the discount factor. The specification follows Brock and Taylor (2003) and is consistent with the existence of a balanced growth path. Observe that preferences are defined over consumption and the global flow of pollution P_t, which enters negatively in the utility function. Additionally, a minimum level of environmental quality is needed to ensure positive welfare and second, whenever pollution reaches its lower bound, there is no marginal gain from less pollution

$$
\begin{aligned}
\lim_{P\to\infty} U(C,P) &= -\infty, \\
\frac{\partial U(C,\underline{P})}{\partial(-P)} &= 0.
\end{aligned}
$$

[11]In addition this attribute of indirect growth in abatement techniques is technically needed to generate a balanced growth path where both sectors will be active within the economy.

These features of the utility function let me define an environmental disaster as the following:

Definition 3.1. *An environmental disaster occurs whenever* $P_t \to \infty$.

Finally, to close the model, the economy's resource constraint is given by

$$C_t^i + X_t^i \leqslant Y_t^i, \tag{3.9}$$

where X_t^i denotes aggregate spending on machines.

3.3.2 Laissez-Faire Equilibrium

A dynamic equilibrium is given by a sequence of prices for inputs (p_{jt}^i), wages (w_{jt}^i), prices for machines (p_{jmt}^i), demand for machines (x_{jmt}^i), demand for intermediates (Y_{jt}^i), demand for manufacturing labor (L_{jt}^i), research allocations of scientists (s_{ct}^i, s_{dt}^i), the flow of local and global pollution (P_t^i, P_t) and the stock of abatement techniques (ABT_t^i) such that in each period t: (i) ($p_{jmt}^i; x_{jmt}^i$) maximizes profits of the entrepreneur of machine m in sector j in country i, (ii) (L_{jt}^i) maximizes profits of producers of intermediate j in country i, (iii) Y_{jt}^i maximizes profits of the final good producer in country i, (iv)(s_{ct}^i, s_{dt}^i) maximizes expected profits of an entrepreneur in country i at time t, (v) w_t^i and p_{jt}^i clear labor and input markets, (vi) and finally, the evolution of local and global pollution is given by (3.5) and (3.7) and (vii) abatement evolves according to (3.6).

Assumption 3.1.

Within both countries $i \in \{N, S\}$ *dirty technologies are initially more developed than clean technologies, such that* $\frac{A_{c,t=0}^N}{A_{d,t=0}^N} < \min\left((1+\gamma_d^N)^{\frac{1}{\sigma-1}}\left(\frac{1}{1+\gamma_c^N}\right), (1+\gamma_d^N)\left(\frac{1}{1+\gamma_c^N}\right)^{\frac{1}{\sigma-1}}\right)$, *and* $\frac{A_{c,t=0}^S}{A_{d,t=0}^S} := \frac{a_{d,t=0}^S}{a_{c,t=0}^S}\frac{A_{c,t=0}^N}{A_{d,t=0}^N} < \min\left((1+\gamma_d^S)^{\frac{1}{\sigma-1}}\left(\frac{1}{1+\gamma_c^S}\right), (1+\gamma_d^S)\left(\frac{1}{1+\gamma_c^S}\right)^{\frac{1}{\sigma-1}}\right)$.

Assumption 3.2.

In both sectors, the technological frontier is defined by the North: $A_{c,t=0}^S < A_{c,t=0}^N$, *and* $A_{d,t=0}^S < A_{d,t=0}^N$.

First we consider the equilibrium at time t for given technology stocks: A_{dt}^i, A_{ct}^i. The final good Y_t^i is produced competitively such that the relative price of the two intermediate inputs can be written as[12]

$$\frac{p_{ct}^i}{p_{dt}^i} = \left(\frac{Y_{dt}^i}{Y_{ct}^i}\right)^{\frac{1}{\epsilon}}, \tag{3.10}$$

[12] Appendix C.1 provides the detailed equilibrium analysis.

where at each point in time I normalize the price of the final good to one, i.e.

$$1 = \left[\left(p^i_{dt}\right)^{1-\epsilon} + \left(p^i_{ct}\right)^{1-\epsilon} \right]^{\frac{1}{1-\epsilon}}. \tag{3.11}$$

Using this, profits for an entrepreneur in sector j in country i at time t are given by

$$\Pi^i_{jt} = (1-\alpha)\alpha(p^i_{jt})^{\frac{1}{1-\alpha}} L^i_{jt} \left(1+\gamma^i_j\right) \left(A^i_{j,t-1}\right)^{1-\phi-\delta} \left(\bar{A}_{j,t-1}\right)^{\delta} \left(A^i_{max,t-1}\right)^{\phi}. \tag{3.12}$$

To determine the direction of technical change, the relative profits between sectors are decisive

$$\frac{\Pi^i_{ct}}{\Pi^i_{dt}} = \left(\frac{p^i_{ct}}{p^i_{dt}}\right)^{\frac{1}{1-\alpha}} \frac{L^i_{ct}}{L^i_{dt}} \frac{A^i_{ct}}{A^i_{dt}}. \tag{3.13}$$

The larger the ratio, the greater the profitability of R&D investments into the clean sector. (3.13) shows that relative profits are a function of the relative stock of existing knowledge, relative prices and the relative market size of sectors. The market size effect pushes innovation towards the more advanced sector, the price effect pulls innovation towards the less-developed sector. While these are standard in the growth literature, there exists an additional direct productivity effect. Through the path dependency of technical progress, further innovations are pulled towards the more developed sector. Empirical evidence for the presence of the "standing on the shoulders of giants" effect is most recently documented in Aghion *et al.* (2011) by studying the direction of research in the car industry.

In equilibrium, the relative profits can be expressed as a function of the mass of scientists s^i_{ct} working in the clean sector and the relative stock of technologies

$$\frac{\Pi^i_{ct}}{\Pi^i_{dt}} = \left(\frac{1+s^i_{ct}\gamma^i_c}{1+(1-s^i_{ct})\gamma^i_d}\right)^{\sigma-2} \frac{1+\gamma^i_c}{1+\gamma^i_d} \left(\frac{A^i_{c,t-1}}{A^i_{d,t-1}}\right)^{\sigma-1}, \tag{3.14}$$

where $\sigma = (1-\alpha)\epsilon + \alpha$ denotes the (derived) elasticity of substitution between factor inputs.[13] Under Assumption 3.2 and the form of technical progress, as stated in equations (3.3) and (3.4), the relative country-specific stock of technologies is given by

$$\frac{A^i_{c,t-1}}{A^i_{d,t-1}} = \left(\frac{A^i_{c,t-1}}{A^i_{d,t-1}}\right)^{1-\delta-\phi} \left(\frac{\bar{A}_{c,t-1}}{\bar{A}_{d,t-1}}\right)^{\delta} \left(\frac{A^i_{max,t-1}}{A^i_{max,t-1}}\right)^{\phi}. \tag{3.15}$$

These equations show that relative profits depend on the existing relative stock of tech-

[13]Note that $\epsilon > 1$ implies that $\sigma > 1$.

nologies, the relative distance to the frontier technology, the size of the spillover effects and the mass of scientists working within each sector. While for the technological leading country, the North, relative profits unambiguously increase in the relative stock of technologies, there exists a trade-off for the technology follower. The "standing on the shoulders of giants" force pushes research to the more developed sector, while the "distance to frontier effect" pulls innovation to the less-developed sector. The larger the distance to the frontier, the larger the obtainable profits within this sector. Finally, note that for $\sigma > 2$ relative profits increase in the mass of scientists working in the clean sector (increasing returns), while for $\sigma < 2$ the opposite applies. If $\sigma = 2$, profits are constant in s^i_{ct}. Lemma 3.1 characterizes the direction of research investments:

Lemma 3.1. *An equilibrium exists, where all research is directed to the clean sector at time t whenever $\frac{\Pi^i_{ct}}{\Pi^i_{dt}} = \left(\frac{1+\gamma^i_c}{1}\right)^{\sigma-2} \frac{1+\gamma^i_c}{1+\gamma^i_d} \left(\frac{A^i_{c,t-1}}{A^i_{d,t-1}}\right)^{\sigma-1} > 1$. On the other hand whenever $\frac{\Pi^i_{ct}}{\Pi^i_{dt}} = \left(\frac{1}{1+\gamma^i_d}\right)^{\sigma-2} \frac{1+\gamma^i_c}{1+\gamma^i_d} \left(\frac{A^i_{c,t-1}}{A^i_{d,t-1}}\right)^{\sigma-1} < 1$, in equilibrium all research is directed to the dirty sector. Whenever $\frac{\Pi^i_{ct}}{\Pi^i_{dt}} = 1$ it will be channelled in both sectors (with $s^i_{ct} \in (0,1)$).*

Proof. See Appendix C.1. ☐

From this Lemma it follows that the case of multiple equilibria becomes possible whenever $\sigma > 2$. To rule out indeterminacy of the steady state equilibrium, Assumption 3.3 ensures that all entrepreneurs target the clean sector, whenever multiple equilibria are ex-ante possible.

Assumption 3.3.

If $\sigma > 2$ and $\frac{\Pi^i_{ct}}{\Pi^i_{dt}}(s^i_{ct} = 0) < 1 < \frac{\Pi^i_{ct}}{\Pi^i_{dt}}(s^i_{ct} = 1)$ there exists a unique equilibrium with $s^i_{ct} = 1$.

Laissez-Faire Steady State

Before characterizing the laissez-faire steady state equilibrium, I restrict the parameter space in the following way:

$$\sigma > 2 \tag{3.16}$$

$$\delta < \phi < 0.25 \ if \ \delta = 0, \tag{3.17}$$

$$0 < \delta = \phi < 0.25 \ if \ \delta > 0, \tag{3.18}$$

$$0 < \gamma^S_j = \xi\gamma^N_j \quad \rightarrow \xi < 1. \tag{3.19}$$

(3.16) makes clear that I focus on the case where there is some substitutability between sectoral intermediates, which is the more relevant case as suggested by the literature.[14] (3.17) and (3.18) limit the overall strength of the cumulated spillover and equalize the strength of spillovers across sectors and countries. Finally, (3.19) shows that the Southern growth rate (step-size of innovation) is strictly positive and proportionally smaller compared to the Northern. However, let me emphasize that the Southern rate of technical progress within one sector j may well be greater than the rate of progress in the Northern sector k. Using this, I summarize the steady state dynamics by the following proposition:

Proposition 3.1. *Suppose that* $(1+\gamma_c^i) < (1+\gamma_d^i)^{\frac{\sigma-1+\phi}{\phi(\sigma-1)}}$ *and Assumptions 3.1-3.2 hold, then there exists an unique equilibrium, where all Northern scientists innovate in the dirty sector,* $\left(s_c^N\right)^{SS} = 0$*, and the South imitates in dirty technologies,* $\left(s_c^S\right)^{SS} = 0$*. The North defines the technological frontier within both sectors and within both countries clean technologies are relatively less-developed. The equilibrium distances to frontier and the relative stock of technologies are*

$$\begin{aligned}
a_d^{SS} &:= \frac{A_d^S}{A_d^N} = \left(\frac{1+\gamma_d^S}{1+\gamma_d^N}\right)^{\frac{1}{\delta}}, \\
a_c^{SS} &:= \frac{A_c^S}{A_c^N} = \left(\frac{1+\gamma_d^S}{1+\gamma_d^N}\right)^{\frac{\phi}{(\phi+\delta)\delta}}, \\
\left(\frac{A_c^N}{A_d^N}\right)^{SS} &= \left(\frac{1}{1+\gamma_d^N}\right)^{\frac{1}{\phi}}, \\
\left(\frac{A_c^S}{A_d^S}\right)^{SS} = \left[\frac{1}{1+\gamma_d^S}\left(\frac{A_c^N}{A_d^N}\right)^{\delta}\right]^{\frac{1}{\phi+\delta}} &= \left[\frac{1}{1+\gamma_d^S}\left(\frac{1}{1+\gamma_d^N}\right)^{\frac{\delta}{\phi}}\right]^{\frac{1}{\phi+\delta}}, \\
A_d^N > A_d^S &> A_c^N > A_c^S.
\end{aligned} \tag{3.20}$$

Consumption, technology, wages and output within both countries grow at the constant positive rate of Northern dirty technologies, γ_d^N*. Pollution is increasing at a strictly positive rate such that a global environmental disaster arises.*

Proof. See Appendix C.1. □

This proposition resembles the main result by AABH (2012) in the sense that research activities are targeted towards the more profitable dirty sector whenever no environmental regulations apply. This result carries over to the global framework, where countries are linked through technological spillovers. The next Section analyzes the behavior of Southern entrepreneurs upon the introduction of Northern environmental regulations.

[14] Compare the papers by Hemous (2012) and AABH (2012) to this point.

3.4 Unilateral Environmental Regulation

Assumption 3.4.

At time t the North enforces environmental regulations, such that all Northern scientists are forced to direct research to the clean sector only, $\left(s_{c\tau}^N\right) = 1\,\forall\,\tau\,\in\,[t,\infty)$.

The behavior of the North is straight forward, as Assumption 3.4 makes $\left(s_c^N\right)^{SS} = 1$ the unique long-run outcome. What remains to be determined, is the form of technical progress and the behavior of the South. Through the spillover effect, δ, relative profits of the clean sector increase for the South. At the same time however, the South gets the chance to become the technological leader in the dirty sector, which raises the risk of a dirty production trap. Thus, not only lead different parameter combinations to different long-run outcomes, but initial conditions will be decisive, too. In the following, I first characterize three possible long-run outcomes before turning to a detailed analysis of the transitional path.

3.4.1 Steady State Characterization

1. Imitation of dirty technologies

Proposition 3.2. *Suppose that* $(1+\gamma_c^S) < (1+\gamma_d^S)^{\frac{\sigma-1+\phi}{\phi(\sigma-1)}}\left((1+\gamma_d^S)(1+\gamma_c^N)\right)^{-\frac{1}{2\phi}}$, $\gamma_c^N > \gamma_d^S$ *and Assumption 3.4 holds, then there exists an unique equilibrium, in which all Northern scientists innovate in the clean sector, while the South imitates only the dirty technologies. The North defines the technological frontier within both sectors and the clean sector dominates within both countries. Distances to frontier and technology ratios are given by*

$$\begin{aligned} a_d^{SS} &= \left(\frac{1+\gamma_d^S}{1+\gamma_c^N}\right)^{\frac{1}{\delta}}, \\ a_c^{SS} &= a_d\left(\frac{1}{1+\gamma_d^S}\frac{1}{1+\gamma_c^N}\right)^{\frac{1}{\phi+\delta}}, \\ \left(\frac{A_c^N}{A_d^N}\right)^{SS} &= (1+\gamma_c^N)^{\frac{1}{\phi}}, \\ \left(\frac{A_c^S}{A_d^S}\right)^{SS} &= \left[\left(1+\gamma_c^N\right)^{\frac{\delta}{\phi}}\frac{1}{1+\gamma_d^S}\right]^{\frac{1}{\phi+\delta}}, \\ A_c^N > A_d^N &> A_c^S > A_d^S. \end{aligned} \tag{3.21}$$

Consumption, technology, wages and output within both countries grow at the constant positive rate of Northern clean technologies, γ_c^N. *Local pollution within both countries as well as global pollution converges to its lower bound* $\underline{P}$.

Proof. See Appendix C.1. □

2. Innovation of dirty technologies

Proposition 3.3. *Suppose that* $(1+\gamma_c^S) < (1+\gamma_d^S)^{\frac{\sigma-1+\phi}{\phi(\sigma-1)}}$, $\gamma_c^N < \gamma_d^S$ *and Assumption 3.4 holds, then there exists an unique equilibrium, in which all Southern scientists innovate in the dirty technologies, while the North is forced to imitation in the clean sector. The technological frontier within both sectors is defined by the South and within both countries the dirty sector constitutes the most developed sector. The long-run distances to frontier and technology ratios are given by*

$$\begin{aligned} a_d^{SS} &= \left(1+\gamma_d^S\right)^{\frac{1}{\delta}}, \\ a_c^{SS} &= \left[\left(\frac{1+\gamma_d^S}{1}\right)^{\frac{\phi}{\delta}} \frac{1}{1+\gamma_c^N}\right]^{\frac{1}{\phi+\delta}}, \\ \left(\frac{A_c^N}{A_d^N}\right)^{SS} &= \left[(1+\gamma_c^N)\left(\frac{1}{1+\gamma_d^S}\right)^{\frac{\delta}{\phi}}\right]^{\frac{1}{\delta+\phi}}, \\ \left(\frac{A_c^S}{A_d^S}\right)^{SS} &= \left(\frac{1}{1+\gamma_d^S}\right)^{\frac{1}{\phi}}, \\ A_d^S > A_d^N &= A_c^S > A_c^N. \end{aligned} \tag{3.22}$$

Consumption, technology, wages and output within both countries are growing at the constant positive rate of Southern dirty technologies, γ_d^S. *Pollution is increasing at a strictly positive rate such that a global environmental disaster arises.*

Proof. See Appendix C.1. □

3. Imitating the clean technologies

Proposition 3.4. *Suppose that* $(1+\gamma_d^N) < (1+\gamma_c^S)^{\frac{(\sigma-1)(2\phi+1)}{2\phi}}(1+\gamma_c^N)^{\frac{(\sigma-1)}{2\phi}}$ *and Assumption 3.3 holds, then there exists an unique equilibrium, in which all Northern scientists innovate in the clean sector, while the South imitates the clean technologies. The North defines the technological frontier within both sectors and within both countries the clean sector has become the most developed sector. Distances to frontier and technology ratios are given* *by:*

$$a_d^{SS} = \left(\frac{1+\gamma_c^S}{1+\gamma_c^N}\right)^{\frac{\phi}{\delta(\phi+\delta)}}$$
$$a_c^{SS} = \left(\frac{1+\gamma_c^S}{1+\gamma_c^N}\right)^{\frac{1}{\delta}}$$
$$\left(\frac{A_c^N}{A_d^N}\right)^{SS} = \left(1+\gamma_c^N\right)^{\frac{1}{\phi}} \tag{3.23}$$
$$\left(\frac{A_c^S}{A_d^S}\right)^{SS} = \left[(1+\gamma_c^S)\left(\frac{A_c^N}{A_d^N}\right)^{\delta}\right]^{\frac{1}{\phi+\delta}} = \left[(1+\gamma_c^S)\left(\frac{1+\gamma_c^N}{1}\right)^{\frac{\delta}{\phi}}\right]^{\frac{1}{\phi+\delta}}$$
$$A_c^N > A_c^S > A_d^N > A_d^S$$

Consumption, technology, wages and output within both countries are growing at the constant positive rate of clean Northern technologies, γ_c^N. Local pollution within both countries as well as global pollution converges to its lower bound $\underline{P}$.

Proof. See Appendix C.1. □

3.4.2 The Transitional Path

This section analyzes the transitional path for both countries and pins down the long-run equilibrium that the economies converge to. Since it is decisive whether Southern R&D is inferior in absolute or in relative terms, the analysis is split in two distinct cases (that depend on exogenous parameters only). Since relative obtainable profits are the key determinant of the direction of research and hence the form of transition, I first define relative profits at time t as a function of scientists allocated to the clean sector

$$f(s_{ct}^i) = \left(\frac{1+s_{ct}^i\gamma_c^i}{1+(1-s_{ct}^i)\gamma_d^i}\right)^{\sigma-2} \frac{1+\gamma_c^i}{1+\gamma_d^i}\left(\frac{A_{c,t-1}^i}{A_{d,t-1}^i}\right)^{\sigma-1}, \tag{3.24}$$

which (for $\sigma > 2$) is increasing in s_{ct}^i. Within the static equilibrium (given the stock of technologies: $\frac{A_{c,t-1}^i}{A_{d,t-1}^i}$) the allocation of scientists across sectors is such that

$$s_{ct}^i = \begin{cases} 1 & if\ f(s_{ct}^i = 1) > 1 \\ 0 & if\ f(s_{ct}^i = 1) < 1. \end{cases} \tag{3.25}$$

As Assumption 3.4 ensures that $s_{ct}^N = 1\ \forall t$ for the North, the analysis' focus lies on the allocation of Southern scientists across sectors. Defining $AS_{t-1} := \frac{A_{c,t-1}^S}{A_{d,t-1}^S}$, there exists a threshold value $\bar{k}$ for AS_{t-1}, that determines the equilibrium allocation of scientists across sectors, given by

$$\bar{k} = \left(1+\gamma_d^S\right)^{\frac{1}{\sigma-1}} \frac{1}{1+\gamma_c^S}. \tag{3.26}$$

Using this, the equilibrium allocation of scientists across sectors for the South is characterized in the following Lemma:

Lemma 3.2. *Define* $\bar{k} := \left(1+\gamma_d^S\right)^{\frac{1}{\sigma-1}} \frac{1}{1+\gamma_c^S}$ *and* $AS_{t-1} := \frac{A^S_{c,t-1}}{A^S_{d,t-1}}$*, then the equilibrium allocation of scientists in the South is given by*

$$s_{ct}^S = \begin{cases} 1 & if\ AS_{t-1} > \bar{k} \\ 0 & if\ AS_{t-1} < \bar{k}. \end{cases}$$

Proof. This follows directly from Assumption 3.3 and equations (3.24) and (3.25). □

Case 1: $\gamma_d^S < \gamma_c^N$

As the Southern innovation capacity is inferior to the Northern in absolute terms, it is evident that in the long-run it is forced to imitation. Hence, in the long-run the economies will converge either to the "dirty imitation equilibrium" (as defined in Proposition 3.2) or the "clean imitation equilibrium" (see Proposition 3.4). Assuming both economies to start within a dirty regime, the transitional path then depends on exogenous parameters only. In the North, the ratio of clean technologies, $\frac{A^N_{ct}}{A^N_{dt}}$ starts rising unambiguously.[15] If $\gamma_c^i > \gamma_d^i$, the stock of clean technologies increases also for the South. As the North is very efficient in the new sector, the South profits from that through technology adoption, which raises the profitability of the clean sector globally. Finally, Southern entrepreneurs switch their investment strategy and target the clean sector. The "good" equilibrium described in Proposition 3.4 occurs. Along the transition, the Southern distance to the frontier in the clean sector increases while the effect on the distance to the dirty frontier is ambiguous. Whenever $\gamma_c^i < \gamma_d^i$, the possibility of a *dirty production trap* arises. Starting from $AS_{t=0} < \bar{k}$, the relative profitability of the clean sector increases for both countries.[16] However, if the long-run relative technology ratio is smaller than the threshold, $\bar{k}$, the South converges to the "dirty imitation equilibrium". From the dynamics of AS_t, the

[15] See Appendix C.1 for a detailed analysis of the equilibrium dynamic equations of technologies.

[16] If $AS_{trap} < AS_{t=0} < \bar{k}$, the ratio of clean technologies of the South falls initially. As the adjustment is instantaneously, it falls below the steady state value and then rises again in conjunction with the Northern ratio.

long-run value (conditional on $s_{ct}^S = 0 \ \forall t$) is given by

$$AS_{trap} = \left[\left(1+\gamma_c^N\right)^{\frac{\delta}{\phi}} \frac{1}{1+\gamma_d^S} \right]^{\frac{1}{\phi+\delta}}. \tag{3.27}$$

Moreover, the South is converging to the technological frontier in the dirty sector, such that a_d rises along the transition. The dynamics of a_c is ambiguous in this case.

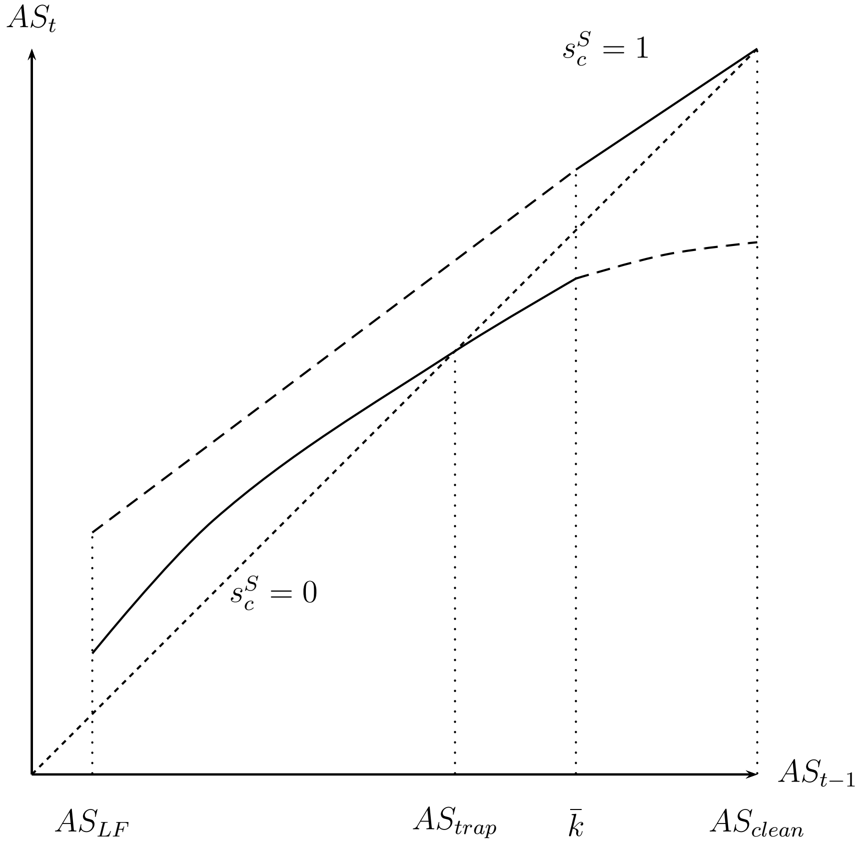


Figure 3.4: Equilibrium Dynamics of AS_t
The figure displays the equilibrium dynamics of AS_t for the case of $\sigma > 2$.

Figure 3.4 visualizes the equilibrium dynamics of the stock of clean technologies AS_t. It assumes the economy to start in the dirty laissez-faire equilibrium and shows the *dirty technology trap* that arises whenever $AS_{trap} < \bar{k}$ (as for the case depicted). Whenever $AS_{trap} > \bar{k}$, at the point where AS_t equals the threshold, the economy switches out of the dirty sector and moves to the clean equilibrium. Upon this, the catching up process in clean technologies is spurred while it is slowed down in the dirty sector. Note that if $a_d > 1$ - as the South may temporarily constitute the technological leader - the distance to the dirty frontier widens again for the South.

When does this become more likely? Note from equations (3.26) and (3.27) that AS_{trap} is decreasing in ϕ, δ and γ_d^S and strictly increasing in γ_c^N. On the other hand the threshold values are decreasing in γ_c^S and increasing in γ_d^S. Hence the *dirty technology trap* is likely to arise within economies with an efficient dirty sector and few possibilities from copying clean technologies. The spillover rate acts as an enforcing parameter such that the relative advantage of the leading sector is strengthened. Moreover $\bar{k}$ is decreasing in the elasticity of substitution σ, such that the switch to the clean sector becomes more likely for a high elasticity of substitution. Intuitively the better the goods are substitutable, the more likely the switch to the clean sector. The next proposition summarizes the equilibrium dynamics:

Proposition 3.5. *Suppose it holds that $\gamma_d^S < \gamma_c^N$, and AS_{trap}, $\bar{k}$ are defined by (3.26), (3.27) and the economy starts within the dirty regime, $s_{c,t=0}^S = 0$, the unique dynamic equilibrium is as follows:*

1. *If $AS_{trap} < \bar{k}$, the economy starts within the regime of full dirty imitation, and converges towards the dirty imitation steady state defined by Proposition 3.2.*

2. *If $\bar{k} \leqslant AS_{trap}$, the economy starts within the regime of full dirty imitation, but switches to the clean sector when $AS_t = \bar{k}$. In the long-run the South converges to the clean imitation steady state described under Proposition 3.4.*

Proof. See Appendix C.1. □

Case 2: $\gamma_d^S > \gamma_c^N$

First, as the South is more efficient in innovation, whenever the Southern scientists are employed in the dirty sector, they must innovate in the long-run. The possibility of the South overtaking the North in the dirty sector, (as well as in the clean sector), leads to the fact that the dynamics of technology ratios change as soon as the South becomes superior. In contrast to the previous case - where parameter conditions determined the long-run outcome - multiple steady states are possible. The long-run equilibrium thus depends on the initial distance to frontier, which emphasizes the importance of the timing of environmental policies.
Along the transitional path the relative stock of clean technologies is increasing within both countries which raises its profitability also within the South. The counteracting effect however occurs, as the South approaches the dirty technological frontier. If the South is initially close to the technological frontier (in dirty technologies), it soon starts innovating in this sector. If this occurs before the investment in the clean sector becomes profitable (i.e. AS_t reaches the critical threshold $\bar{k}$), an environmental disaster becomes inevitable. Upon the South switching from imitation to innovation in the dirty sector, the dynamical system changes. Then the relative stock of clean technologies decreases again (for the South) and the distance to the clean frontier widens (as the spillover channel is

shut down). However, since the spillover within countries is still active, in the long-run the South must overtake the clean frontier as well. Upon this, the North is increasingly influenced by Southern technologies, which on the one hand leads to a decline of the relative stock of clean technologies even in the North, but on the other hand reduces its distance to the dirty technology frontier. Naturally, as the North is inefficient in innovating clean technologies, the South prefers own innovation over adopting the clean ones from the North. The combination of the market size for dirty technologies and the incentive to become the technological leader within one sector drives the result of the *dirty technology trap*. But even if in this case the environmental disaster is inevitable, bear in mind that this result is specific for the South being already very close to the dirty technological frontier when the North imposes environmental regulations. On the other hand, if the South starts very far from the technological frontier, the clean technologies continue to catch up and the transition depends again on the relation between $AS_{trap} \lesseqgtr \bar{k}$. If $AS_{trap} < \bar{k}$, the dynamics and the long-run equilibrium is the same as above. If $AS_{trap} > \bar{k}$, Southern entrepreneurs switch sectors as soon as investment in clean technologies is (more) profitable. Upon the regime switch, the clean distance to the frontier decreases, while the distance to the dirty frontier increases again. The ratio of clean technologies keeps rising throughout until the new steady state (see Proposition 3.4) is reached.

Figure 3.5 plots the equilibrium dynamics of the stock of clean technologies, AS_t, visualizing two possible transitional dynamics depending on the South's initial backwardness.[17] Starting from the laissez-faire technology ratio, denoted by AS_{LF}, the lower solid line displays the transitional path for a country being close to the technological frontier. The growth in the relative stock of clean technologies is minor and convergence to the new steady state value, denoted by AS_{IN}, is fast. Since $AS_{IN} < \bar{k}$, the economy is locked-in the *dirty technology trap*. In contrast, the upper solid line displays the transitional path for an economy starting far from the technological frontier. For this economy the transitional period is much longer, which gives Northern clean technologies the chance to spill over to the South and hence increase the profitability of clean R&D. As $\bar{k} < AS_{trap}$, (which is the case depicted) Southern entrepreneurs follow the North and change the direction of their R&D investments. The South then converges to the "good" equilibrium, where AS_{clean} denotes the new steady state technology stock. Finally, whenever $\bar{k} > AS_{trap}$, the South will stick to specializing in dirty production technologies, independent of the initial distance to frontier. Thus, the combination between parameter specifications and initial conditions determine the long-run equilibrium. The following proposition summarizes the equilibrium dynamics:

[17] Again, the figure assumes the starting point to be the dirty laissez-faire equilibrium.

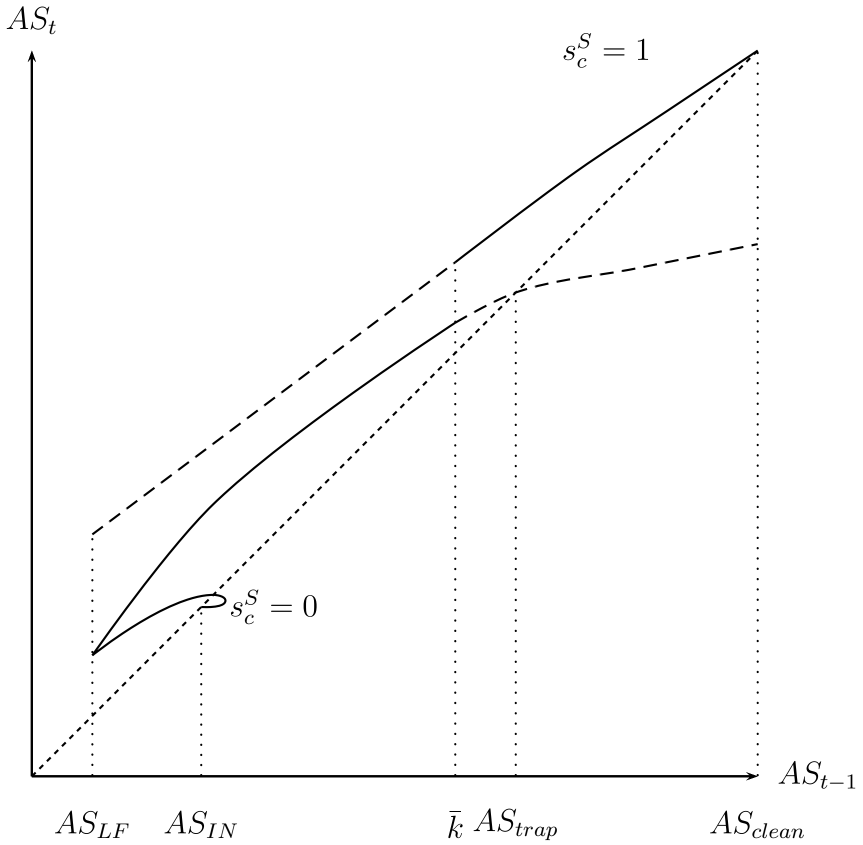


Figure 3.5: Equilibrium Dynamics of AS_t

The figure displays the equilibrium dynamics of AS_t for the case of $\sigma > 2$.

Proposition 3.6. *Suppose it holds that $\gamma_d^S > \gamma_c^N$, and AS_{trap}, $\bar{k}$ are defined by (3.26), (3.27) and the economy starts within the dirty regime, $s_{c,t=0}^S = 0$, the dynamic equilibrium is as follows:*

1. *Whenever $AS_{trap} < \bar{k}$, the economy starts within the regime of full dirty imitation, and converges towards the dirty innovation steady state defined by Proposition 3.3, independent of the initial conditions.*

2. *Whenever $AS_{trap} \geqslant \bar{k}$, multiple steady states are possible depending on the initial distance to frontier in dirty technologies: let T^1 denote the number of periods it takes the South to reach the technological frontier, $a_{dt} = 1$, and let T^2 denote the number of periods it takes the ratio of technologies to reach the critical threshold, that is $AS_t = \bar{k}$. Whenever $T^1 < T^2$ the South converges to the dirty innovation steady state as described under Proposition 3.3.*
   Whenever $T^1 \geqslant T^2$, the economy starts within the regime of dirty imitation, but switches to the clean sector when $AS = \bar{k}$ and in the long-run converges to the clean imitation steady state described under Proposition 3.4.

Proof. See Appendix C.1. □

3.5 Discussion and Numerical Illustration

3.5.1 Discussion

The Dirty Imitation Equilibrium

Proposition 3.2 shows that although Southern scientists keep targeting the dirty sector, clean technologies have overtaken the country-intern technological frontier. This is triggered by the South being extremly inefficient in R&D activities (low γ_j^S), such that the indirect effect of cross-country spillovers dominates the direct effect of active imitation in the dirty sector.

There is no scope for the South to leapfrog the technological leading North, not even in the dirty sector. However, as the growth rate of clean technologies is small, the incentive to copy clean technologies from the leading country is not strong enough. For this equilibrium to exist, it must be that $\gamma_c^i < \gamma_d^i$, such that the clean sector is less attractive as such. Moreover, from equations (3.26), (3.27) note that the South must only be marginally less effective, $\gamma_d^S \approx \gamma_c^N - \epsilon$, and intermediates are not very good substitutes, $\sigma \approx 2$. Interpreting these findings, the equilibrium is likely to arise within developing economies, that do not impose environmental regulation and entrepreneurs that do not internalize the negative externality of pollution. However, as countries are not capable of own innovation, they rely on adopting technologies from the North. Thus, through the link of technology adoption, clean technologies diffuse to the South such that unilateral environmental regulations in the frontier country are enough to prevent the environmental disaster. This is the result discussed in Di Maria and Smulders (2004) and mainly applies to developing countries that are far from the technological frontier. From the environmental point of view both economies profit from unilateral environmental regulations as they are shifted to a sustainable growth path. Local as well as global pollution is decreasing at a positive rate and converges towards its lower bound $\underline{P}$. From an economic point of view regulations do not lead to a negative growth drag in output, however, since $\gamma_c^N < \gamma_d^N$ and the South relies on imitation, the long-run growth rate of both economies is reduced.[18]

The Dirty Innovation Equilibrium

Being the focus of this paper, this equilibrium arises, whenever innovation activities in the dirty sector are sufficiently advanced and the country is close to the technological frontier. In Section 3.2, I documented that this is the relevant case for emerging markets like China. In the North environmental regulations prevent further R&D investments in the dirty sector, which gives the technological follower the chance to approach the technological frontier and take the leading position. Moreover, since clean technologies are inferior, there is no incentive for the Southern entrepreneur to adopt them when she can invent a more productive (dirty) one. Through path dependency of technological progress the more advanced dirty sector then attracts all R&D investments. By reaching the dirty technological frontier, the incentives to push these technologies further and to become the technological leader within this sector strengthens the relative profitability even more. As part of the acquired new knowledge is fundamental to research in general, the Southern clean sector also profits in the long-run, finally overtaking the clean frontier as well. From this point onwards, the North is forced to imitate the few clean technologies developed in the South. Thus, the closer the unregulated country to the technological frontier, the larger the probability of an environmental disaster, where the role of the technological leader becomes reversed. This has severe consequences in economic and environmental terms. Economically, the North suffers twice: (i) first, the long-run growth rate is reduced and (ii) second, only by imposing environmental regulations, the South is able to overtake the North in terms of output, technology and consumption. However, note that the long-run growth rate within both countries is strictly larger than in the equilibrium of dirty imitation (see above). Finally, as the dirty technologies are the most developed ones, pollution is rising towards infinity such that unilateral environmental

[18] The direct effect on welfare however is not straight forward as agents benefit from less pollution.

regulations fail to prevent a global disaster. Both economies are on an unsustainable growth path.[19] Note that even though the North innovates in the clean sector, their research is too inefficient to change the technology composition used within the country.

The Clean Imitation Equilibrium

This equilibrium marks the "good" long-run steady state, in which unilateral environmental regulations are sufficient to prevent an environmental disaster. Since the North is efficient in developing clean technologies, the attractiveness of investments in the clean sector increases even within the unregulated South. Through the cross-country spillover, the Southern clean sector benefits from a high growth rate in the North such that the relative dominance of dirty technologies is reduced. As the relative stock of clean technologies rises, profitability of the clean sector is increased, such that finally Southern entrepreneurs switch their direction of research to the clean sector as well. Clearly, from the environmental perspective this is the desired outcome as all research is directed towards non-polluting technologies. Economically, the consequences are ambiguous: depending on the relation between clean and dirty growth rates, the long-run growth rate of both economies can be greater or smaller than in laissez-faire. While this equilibrium is the preferred outcome in the North, it is unclear whether the South favors this regime. Compared to the dirty innovation equilibrium, the South is not able to become the technological leader, and the long-run growth rate is smaller than in the previous case (conditional on $\gamma_d^S > \gamma_c^N$).

3.5.2 Numerical Illustration

In this section I illustrate the transitional dynamics for the two distinct cases, $\gamma_d^S \lessgtr \gamma_c^N$. Before I define the necessary parameters required, let me emphasize that this is an illustrative exercise and exact values of parameters should not be taken (too) seriously. I follow AABH (2012) and set $\alpha = \frac{1}{3}$, such that the share of machines in the production function equals the usually assumed capital share. Moreover, I set $\gamma_d^N = 0.02$ such that the long-run growth rate (in the past) is about 2% p.a., which is again in line with the literature. Motivated by the currently slower growth of clean technologies, I choose $\gamma_c^N = 0.01$ such that the regime under environmental regulation enjoys a slower equilibrium growth rate of 1% p.a. Further, I fix the spillover parameters with $\phi = \delta = 0.1$. As the absolute value of initial technology levels, $A^i_{j,t=0}$ does not matter for the long-run outcome,

[19]Interpreting these findings as evidence for environmental quality being a luxury good, may lead to the dangerous conclusion that all countries eventually switch to a sustainable growth path. However, to avoid the environmental disaster, it would require an unreasonable small rate of environmental degradation and a tiny growth rate of emissions. Empirical evidence tells exactly the opposite, stressing the importance of the immediate enforcement of environmental policies.

I only need to fix the ratios of technologies within each country. For this I assume that the relative stock of technologies within each country equals the laissez-faire steady state value and define $AN_t := \left(\frac{A^N_{c,t=0}}{A^N_{d,t=0}}\right) = \left(\frac{1}{1+\gamma^N_d}\right)^{\frac{1}{\phi}}$ and $AS_t := \left(\frac{A^S_{c,t=0}}{A^S_{d,t=0}}\right) = \left[\frac{1}{1+\gamma^S_d}\left(\frac{1}{1+\gamma^N_d}\right)^{\frac{\delta}{\phi}}\right]^{\frac{1}{\phi+\delta}}$. Finally, ξ, $a_{d,t=0}$ and ϵ, will vary depending on the case I consider.[20]

1. $\xi = 0.49 \Rightarrow \gamma^S_d < \gamma^N_c$: as analyzed in Section 3.4.2, the long-run equilibrium will be determined by parameters independent of initial conditions. As the South is less efficient in research, it will never overtake the North as the technological leader, but always stay behind. Thus, all Southern entrepreneurs either perform dirty imitation or clean imitation in the long-run.[21] I fix the distance to the dirty technological frontier to $a_{d,t=0} = 0.3$ such that the South starts off with having acquired 30% of the technologies available in the North. Then I let ϵ vary to generate two possible transitional paths. Figure 3.6 visualizes the equilibrium dynamics for the two relative technology stocks, AS_t, AN_t and the two distance to frontier measures, a_{ct}, a_{dt}. The upper panel shows the dynamics for the case of $\epsilon = 2.5$, while the lower one shows the dynamics for the case of $\epsilon = 10$. While the first case leads to the long-run steady state of continued imitation in the dirty sector, the second case generates the "good" equilibrium, in which all Southern entrepreneurs find it optimal to follow the North in the clean sector. Thus, the degree of substitutability between intermediate inputs is decisive, which was already stressed in AABH (2012). For intermediates being good substitutes, the Southern entrepreneur is more willing to switch to the new technology, upon which the relative stock of clean technologies rises, the distance to the clean frontier decreases and the distance to the dirty frontier becomes slightly larger again. Note that the path of AN_t is the same in both scenarios as the North remains the innovator and hence independent of the path of Southern technologies.

[20] Note that $a_{c,t=0}$ then is indirectly fixed through the relative technology stocks within countries, i.e. $a_{ct} = a_{dt}\left(\frac{A^S_{c,t=0}}{A^S_{d,t=0}}\right)\left(\frac{A^N_{c,t=0}}{A^N_{d,t=0}}\right)^{-1}$.

[21] However, note that along the transition there may exist a limited period, in which the South constitutes the technological frontier in dirty technologies.

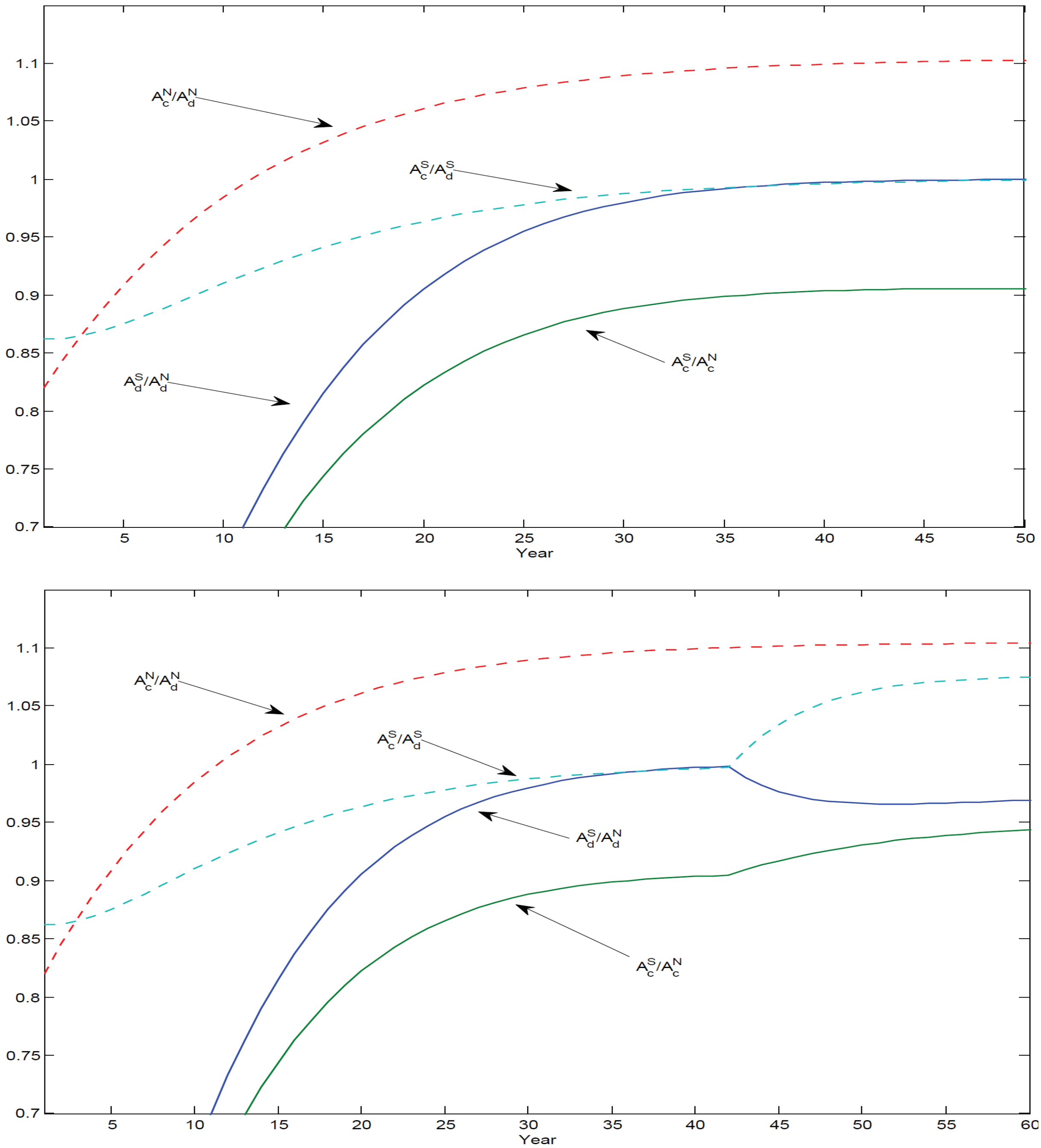


Figure 3.6: **Equilibrium Dynamics**

The figure displays the equilibrium dynamics of AN_t, AS_t, a_{ct} and a_{dt} for the case of $\gamma_d^S < \gamma_c^N$.

2. $\xi = 0.52 \Rightarrow \gamma_d^S > \gamma_c^N$: in contrast to the previous case, now initial conditions are the key determinant of the long-run equilibrium (possibly together with parameter conditions). I fix $\epsilon = 10$, such that $AS_{trap} > \bar{k}$ and only the initial distance to frontier will decide which long-run equilibrium the economy converges to.[22] Thus, I let $a_{d,t=0}$ vary to visualize both possible cases. The upper panel in Figure 3.7 shows the case for emerging markets that are close to the technological frontier, starting with $a_{d,t=0} = 0.6$. The South very quickly becomes the technological leader (in dirty technologies) and from then on innovates at the frontier more efficiently than the North does in clean technologies. Naturally then, clean technologies never can compete with the stock of (already) available dirty technologies. In this scenario there is a long intermediate period, in which the North innovates at the clean and the South innovates at the dirty frontier. However, since the Southern growth rate is larger in absolute terms, it finally overtakes the clean technological frontier as well. Upon this the North falls behind and is forced to imitation. In contrast, the lower panel in Figure 3.7 displays the case for countries that start far away from the technological frontier with $a_{d,t=0} = 0.1$. Through the technological spillover profits in the dirty sector get depressed and after a relatively short interval profits in the clean sector have risen sufficiently, such that the South follows the North in clean R&D even though it foregoes the chance to become the leader in world technologies. Note that this scenario is very similar to the one depicted in the lower panel of Figure 3.6.

[22] I focus on $\epsilon = 10$ since for $\epsilon = 2.5$ there exists only one feasible long-run equilibrium.

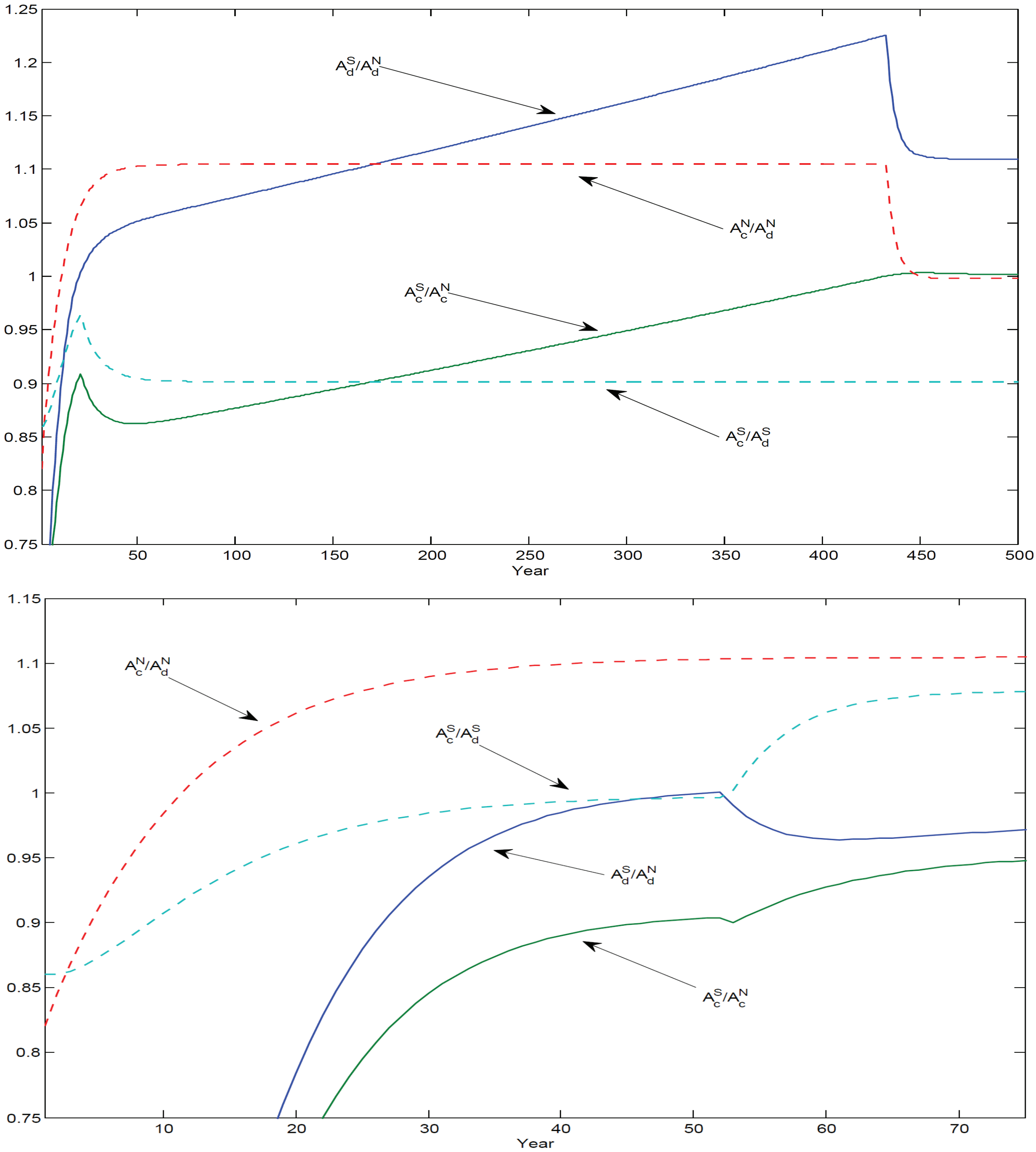


Figure 3.7: **Equilibrium Dynamics**

The figure displays the equilibrium dynamics of AN_t, AS_t, a_{ct} and a_{dt} for the case of $\gamma_d^S > \gamma_c^N$.

3.6 Conclusion

Assuming unilateral environmental regulations within the industrialized world, this paper characterized the optimal behavior of profit-maximizing entrepreneurs in non-regulated emerging market economies. Analyzing the direction and form of technological progress, the model allows for a sector-specific cross-country spillover as well as for an intra-country cross-sector spillover. Letting growth rates be different across countries and sectors and interacting them with the spillover parameters, embeds the analysis in a very general set-up. Abstracting from interior equilibria, three different long-run outcomes are possible, depending on the relation between growth rates, the substitutability between factors of production, the strength of the spillovers and the initial distance to the (dirty) technological frontier. Emerging markets close to the technological frontier that are capable of innovation raise the risk of a global environmental disaster. Since the polluting sector is their most developed one, and technological progress features path dependency, innovation is directed towards the "dirty" sector only. By targeting the more profitable dirty sector, they are able to overtake the global technological frontier and the environmental disaster is unavoidable. In contrast, less developed countries where technological progress occurs through adoption of frontier technologies, are more prone to follow the regulated industrialized world and switch to installing non-polluting technologies. Since clean technologies are growing faster, profit maximization is enough to push all research towards the clean sector. Finally, countries that are close to the frontier but are incapable of innovation, face a mixed outcome. Although they still direct research investments in the dirty sector, diffusion of clean technologies from the industrialized countries is strong enough to prevent a global environmental disaster. This shows that unilateral regulations are sufficient to prevent a disaster only if (i) the technological leading country is the one that enforces regulations and (ii) the rate of cross-country technology diffusion is sufficiently high. Judging from China's R&D accounts however suggests that emerging markets are already close to the stage from where innovation becomes the driving force of technological progress. From an economic point of view desirable, for the global environment it will be devastating, if emerging markets that lack the enforcement of environmental policies become the global technological leader. Hence, this study supports the call for an immediate enforcement of environmental regulations on a global scale.

4 Demand Forces of Technical Change Evidence from the Chinese Manufacturing Industry

Joint with Andreas Beerli, Fabrizio Zilibotti and Josef Zweimüller

4.1 Introduction

To which extent does the emerging middle class fuel growth and technical change in the Chinese manufacturing industries? The unprecedented growth in average incomes in China since the outset of its economic reforms in 1978 lifted over half a billion people out of poverty. The process was associated with the emergence of a new class of consumers with discretionary income to spend on consumer goods that satisfy less basic needs. This paper asks whether and to which extent the expected expansion of the local market for consumer durables might have stimulated productivity-enhancing investments by Chinese firms, thus partly contributing to an explanation of the surge of technical progress in Chinese manufacturing.

Our empirical investigation is motivated by recent theories of growth with directed technical change (e.g., Acemoglu and Zilibotti, 2001; Acemoglu, 2002, henceforth DTC) and with non-homothetic preferences (Foellmi and Zweimüller, 2006; Boppart, 2011, henceforth NHP). The theory of DTC predicates that firms' investments in new technologies hinge on a market size effect: as the demand for a good produced by a particular industry increases, firms in such an industry invest more in the creation or adoption of new technologies relative to industries in which demand is sluggish. The theory of NHP predicts, in turn, that economic growth affects the sectoral composition of domestic demand. It is well-known, for instance, that economic development and the formation of a middle class reduces the food share of consumption and stimulates the demand of durable consumption goods. If, in addition, there is a hierarchy in the consumers' purchase of durable good (e.g., as they grow richer, households purchase first a motorbike, and then a car) the process of economic growth is characterized by waves of expansion of the domestic market for different durable goods. Merging the insight of the two theories yields the prediction that economic growth brings about demand-driven waves of technical progress: the expectation of a future market size expansion for the product of a particular industry causes a boom in innovative activities in that industry.[1]

To establish an empirical link between expected market size and technical progress, we combine data from two different sources: the Chinese Health and Nutrition Survey (CHNS) which provides information on consumption behavior of households; and the Annual Survey of Industrial Production (ASIP) from which firm-specific productivity measures (and their changes over time) can be calculated. We concentrate on 16 industries covering a substantial share of expenditures for consumer durables: cellphones, cars, computers, telephones, refrigerators, home video appliances, washing machines, air conditioning, cameras, satellite dishes, motorcycles, kitchen appliances, radios, sewing machines, electric fans and cycles.

A potential problem with our empirical analysis is the endogeneity of market size. Technical progress can be the trigger rather than the effect of the expansion in the domestic market of a specific product, e.g., by causing a fall in its sale price. To tackle the endogeneity problem we exploit the large variation in the households' distribution across income classes associated with the Chinese economic growth during the last two decades: in 1990 less than one percent of Chinese households fell into the category of high-middle income and high-income households, while both low-income and low-middle income households made up close to 50 percent each.[2] By the year 2009, the fraction of low-income and low-middle income households has fallen below 10 percent and to 40 percent, respectively, while the fraction of high-middle and high-income households has increased to more than 30 percent and 20 percent, respectively. These changes lead to predictable, differential changes in demand across various consumer goods industries. For instance, to return to the previous example, the market for motorcycles booms earlier than the market for cars. However, at some point, the former becomes saturated, and the potential for future market expansion dies off. At that point, it is the car industry that starts attracting investments and innovative activities. It is this source of variation that forms the basis of our strategy to identify the impact of expected demand on technical change in Chinese manufacturing industries.

More precisely, we construct product-specific Engel-curves for the 16 consumer durables, and estimate changes in expected market size for each durable good. We first fix income-

[1] A formal argument of the link between DTC and NHP is provided in the recent theory of structural change of Boppart and Weiss (2013)

[2] Following World Bank convention, we group households into four classes: low-income, low-middle income, high-middle income, and high-income. The corresponding income brackets – measured in real incomes per year in constant 2009 Yuan - are: 0-2'149 Yuan; 2'150-8'514 Yuan; 8'515-16'499 Yuan; and 16'500 Yuan or more. (Measured in 2009 US $ this corresponds to US $ 0-2'149; US $ 2'150-4'167; US $ 4'168-8'075; and US $ 8076 or more.)

group specific ownership rates of a particular durable good to a particular base-year and then use the changing population shares across income classes to calculate a measure of potential ownership and potential market size in other years. This yields an industry-specific markets size measure, whose evolution over time is entirely driven by changes in the income distribution. Changes in ownership patterns of a given income group, which might be induced by changes in prices or the quality of goods, do not affect this potential market size measure. To the extent that these differential changes in expected markets size are uncorrelated with unobserved factors that drive innovation incentives, our market size measure identifies the impact of expected demand on technical change in Chinese manufacturing.

We find quantitatively important demand effects on technical change: a one percent increase in expected market size increases firm-specific TFP by 0.27% and firm-specific labor productivity by 0.42%. Hence our findings suggest that firms in industries with a large expected local market are significantly more productive today, and show higher levels of other measures of innovative activity. Moreover, the effect of expected market size becomes larger when the expected market size measure is constructed from a longer time window over which firms may form expectations about local market size.

The estimated effect of expected market size is robust to a number of checks. First, we include a rich set of firm-level determinants of R&D and market concentrations, in particular foreign and government ownership, as some scholars pointed out that this may affect productivity to a considerable degree (Van Reenen and Yueh, 2012). Second, we show that our results are robust to supply-side drivers of R&D affecting innovation opportunities of Chinese firms by including a measure of worldwide technology potential reported by Swiss firms. Third, our findings our robust when we control for a firms' export status. This is particularly important in the context of China, as the Chinese economy is strongly export-driven, so demand conditions on export markets may be more relevant for productivity and technical progress than domestic demand. We test for the robustness of our results controlling for firms' export behavior. Interestingly, in our dataset there is a stark dichotomy between exporting and non-exporting firms. About 50% of the firms in our sample do not export at all, whereas for 24% of them exports account for more than 75% of their total sales.[3] Interestingly, we find that the domestic market size effect is totally insignificant for exporting firms. Instead, our results are driven entirely by non-exporting firms serving exclusively the Chinese market. This is coherent with our hypothesis that innovative activity is driven by the expectations of future market size. For exporting firms what matters is the global market, thus the expansion of the

[3]To be precise, it may be that one firm exports in one year but not in the next year. Shares are taken with respect to the panel of datapoints.

domestic market size is less important. It is instead the technology adoption behavior of non-exporting firms that hinges the most on the expectation of about future domestic demand. For instance, the incentive for a Chinese car producer serving the local market to invest in technology hinges on the expansion of the Chinese middle class. In contrast, this does not matter for an assembling firm producing cameras that are exported to the West.

Empirical studies thoroughly examining the effect of market size on innovation remain relatively scarce with most papers focusing on the pharmaceutical industry. Acemoglu and Linn (2004) document a causal link between market size and innovation building on differential patterns of drug use between young and old individuals. Exploiting the demographic changes in the US population as exogenous source of variation in market size, they find a positive effect of expected demand on innovation across different drug categories. Their findings are quantitatively important and very robust. A one percent increase in potential market size leads to approximately a 4% increase in the entry of new non-generic drugs. Finkelstein (2004) demonstrates that health policies designed to increase utilization of vaccines created strong incentives to develop new vaccines. According to her estimates, a 1 dollar increase in expected annual revenue for vaccines generates additional 6 cents of investment in that vaccine. Moreover, these policies were associated with a 2.5-fold increase in clinical trials for new vaccines. Contrasting evidence comes from Acemoglu *et al.* (2006) who investigate the effect of Medicare on the development of new pharmaceuticals for the elderly. They find no evidence that the introduction of Medicare is associated with an increase in drug consumption among the elderly. Consistent with this, they also find no evidence of an increase in the approval of new drugs more likely to treat diseases that affect the elderly, after Medicare's introduction. Blume-Kohout and Sood (2012) consider the market size increase for prescription drugs through Medicare Part D which increased pharmaceutical firms' expected sales. They find a significant increase in pharmaceutical R&D for therapeutic classes with a higher Medicare market share. De Mouzon *et al.* (2011) use detailed data on spending patterns of patients (and their insurers) to show that expected market size has a highly significant and quantitatively important effect on innovations (as measured by the number of new chemical entities of the market of a particular disease class).

The above findings all indicate a large impact of expected market size on innovative activities but they are specific to the pharmaceutical industry. It is not clear whether empirical evidence from the pharmaceutical industry applies to other industries as well. The recent study by Boppart and Weiss (2013) focuses on demand effects on R&D in the whole US industry. Using the input-output structure of different industries as an instrument for actual market size, it turns out that a sector's market share has a significant positive effect on sector-specific R&D investments.

Our paper is also related to the literature studying the determinants of the recent sharp increase in R&D and patent activity in China. The share of R&D expenditure on GDP roughly tripled in China from 0.6% in 1996 to over 1.8% in 2011 (The World Bank 2014). While an increase in R&D intensity is a common pattern over the development process, this has started when China has still a very large technology gap from the frontier. Taiwan, for comparison, reached the same R&D-to-GDP ratio in 1995 as did China in 2009, when its GDP per capita was twice as large as China in 2009. Some recent studies argue that this exceptional pattern is partly due to the opportunities provided by the presence of a large domestic market. Gao and Jefferson (2007) argue that large and fast growing consumer markets create a premium for research-intensive industries to establish production centers in close proximity to burgeoning-consumer markets. Hu and Jefferson (2008) go further and suggest that an important driving force could be the changing composition of domestic consumption shifting away from products with low-technology content (such as bicycles) to goods and services that are more technology intensive (such as automobiles).

The rest of the paper is organized as follows. Section 4.2 describes our data sources and provides some descriptive statistics. Section 4.3 explains the econometric model and lays out our empirical strategy. Section 4.4 presents the baseline results and Section 4.5 discusses a variety of robustness checks. Finally, Section 4.6 concludes.

4.2 Data and Descriptive Statistics

We use two micro-level data sources. The first contains household-level data about the ownership of durable goods to construct a count measure of actual market size.[4] The second contains firm-level manufacturing data about value-added, investments and employment that we used to estimate total factor productivity, our main outcome measure of innovative investments.

[4]Working with durable goods ownership rather than household expenditure data has some important advantages but also bears some difficulties. The main advantage is that CHNS' coverage of a relatively broad set of different durable goods allows to construct a market size measure with substantial industry and time variation which can be linked relatively straightforward to different industries in the manufacturing data. Second, the lumpy nature of durable goods creates an interesting variation in ownership profiles across the income distribution which can be exploited to create an exogenous measure of market size. As a major disadvantage relative to expenditure data, we have no information about the value of different durable goods. Therefore, we can only use the population count of each durable good in the population and need to abstract from value weighted market size measure. See Appendix D.1.1 for greater detail.

4.2.1 Market Size

The household-level ownership data are from the China Health and Nutrition Survey (CHNS). The CHNS was collected in eight waves between 1989 to 2009, and covers a representative sample of Chinese urban and rural households across nine provinces with substantial variation in geography, economic development and public resources. These data are publicly available and are widely used in the literature.[5] The CHNS contains information, for a number of durable goods, on how many items of a particular durable good are owned by each household, of which we also know the income and household size. We combine this information with the size of the Chinese population to estimate total number of items of a particular durable good j held by Chinese consumers in year t, denoted by $Stock_{j,t}^{actual}$.[6]

Figure 4.1 shows the diffusion patterns of five selected durable goods between 1989 to 2009: cycles, electric fan, refrigerator, air condition, and car. The years not covered by the CHNS are fitted by linear interpolation.[7] The time interval between 1998 and 2007, which we can match to the firm-level data described below, is marked with the dotted vertical lines. Electrical fans were already widespread in the early years, and feature some saturation in more recent years. Saturation is even stronger for bicycles whose stock is decreasing since 2000, likely to be due to their progressive substitution with higher-ranked transportation vehicles such as motorcycles and cars. There is no saturation for refrigerators, air conditioning and cars. The ownership of these durables is booming during the period of our study.

We use the evolution of the ownership stock to infer the flow of newly purchased goods, our proxy for market size. To calculate such a flow we take into account that the per capita stock of each durable good can change for three reasons: (i) some households acquire the good for the first time (extensive margin); (ii) some households who already own units of the good buy additional units (intensive margin); (iii) some households replace worn out items (replacement demand). Assuming a constant replacement rate δ_j yields the following annual flow of newly purchased goods (*actual market size*):

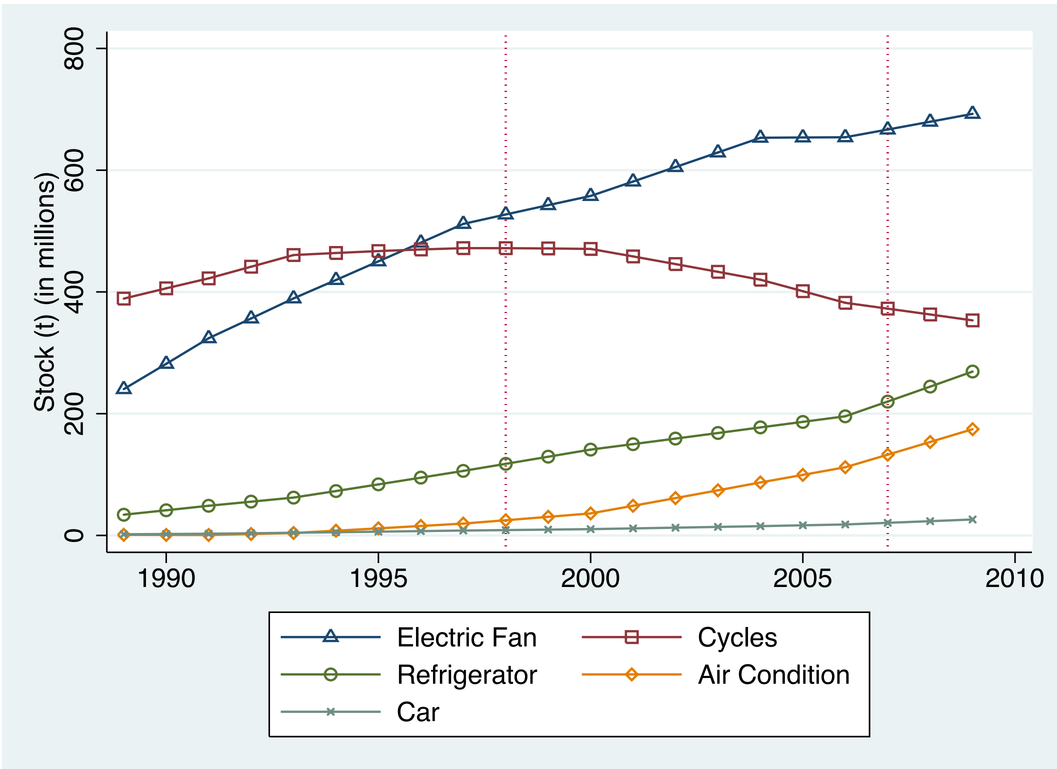
---

[5]See, among others, Benjamin *et al.* (2005), Benjamin *et al.* (2005b), Liu (2008). See Beerli (2010) for a more detailed description of this data set.

[6]The population of China is from the Penn World Tables. More formally, we use the number of items of a specific durable good j in wave t owned by household h, $nrowned_{h,t}$, and the number of household members, $hhsize_{h,t}$, to compute the average number of items per head, i.e. $\left[\frac{1}{H_t}\sum_{h=1}^{H_t}\left(\frac{nrowned_{h,t}}{hhsize_{h,t}}\right)\right]$, where H_t is total number of households in period t. Then, we take the Chinese population size in year t (China Version 1) from the Penn World Tables 7.0, Heston *et al.* (2011), to get $Stock_{j,t}^{actual}$.

[7]"Cycles" are the cumulative ownership of bicycles and tricycles. See Section 4.2.2 for detail.

Figure 4.1: Evolution of Durable Good Stocks



Notes: The figure shows the total items owned (in millions) for each durable good, $Stock_{j,t}^{actual}$, i.e. for electric fans, refrigerators, air conditioners and cars. "Cycles" is the cumulative ownership of bicycles and tricycles. CHNS data 1989 to 2009, years between survey waves linearly interpolated.

$$MS^{actual}_{j,t,t+1} = \underbrace{\left[Stock^{actual}_{j,t+1} - Stock^{actual}_{j,t}\right]}_{\text{new purchases}} + \underbrace{\delta_j \cdot Stock^{actual}_{j,t}}_{\text{replacement purchases}}$$

Unfortunately, the CHNS provides no information about when households decide to scrap existing durable goods. Nor could we find estimates of depreciation of durables for China. We resort to using the depreciation estimates available for the US from the BEA (2003). As shown in Table D.1 (Appendix D.1.3), the BEA (2003) offers depreciation estimates for a large variety of different durable goods for the years 1925 to 1997.[8] We use the average over this long period. We check the robustness of the results to using alternative depreciation rates. The results are robust to a large range of depreciation rates. When the estimate of $MS^{actual}_{j,t,t+1}$ so calculated is smaller than one, we set $MS^{actual}_{j,t,t+1}$ to one.[9]

Figure 4.2 displays the evolution of market size for the five durable goods displayed in Figure 4.1. The electric fan market is stationary; the market for cycles is shrinking; finally the market for refrigerators, air conditioning and cars is increasing.

In our regression analysis below, we use market size over a multi-period horizon. More formally, our market size measure is the yearly average over the relevant period (e.g., $k = 4$ means a five-year horizon taking into account the stock of goods between t and $t + 4$):

$$MS^{actual}_{j,t,t+k} = \frac{1}{k}\sum_{s=0}^{k-1}\left[MS^{actual}_{j,t+s,t+s+1}\right].$$

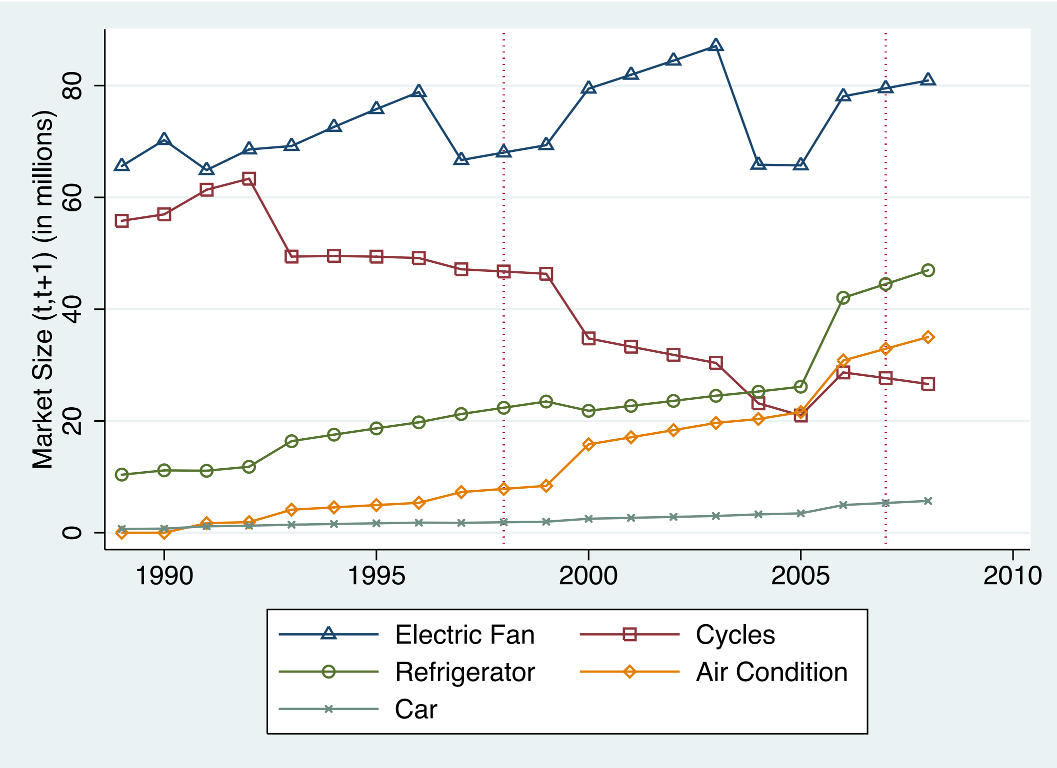
4.2.2 Industrial Production

We use firm-level data from the Annual Survey of Industrial Production (ASIP) 1998-2007. The survey is conducted by the Chinese government's National Bureau of Statistics (NBS). The ASIP is a census of all non-state firms with more than 5 million RMB in revenue

[8]The BEA (2003) estimates the length of service lives (in years) for a large variety of durable goods for years 1925 and 1997. By definition, assets are "retired" from the stock at the end of their service lives. Following the BEA (2003), we set δ_j equal to the inverse of the service life of a durable good j. This represents the share of the total stock of a durable, which needs to be replaced each year, in order to keep the total stock constant.

[9]While this adjustment is somewhat arbitrary, we prefer this route to eliminating negative observations from the sample, as the latter would cause a major selection problem. In the case of negative growth, we set MS^{actual} to unity rather than to zero because in the regression analysis below we take the logarithm of MS^{actual} and this is not defined at zero. To keep the ranking of goods unchanged, this then requires us to set all observations between zero and one to one. Note that this adjustment only concerns two observations of $MS^{actual}_{j,t,t+1}$ of radios in 2004 and 2005. However, in our baseline regressions these two observations are not included as we are interested in the market size effect over a longer time horizon, i.e. $MS^{actual}_{j,t,t+4}$.

Figure 4.2: Evolution of Market Size of Durable Goods



Notes: Actual market size is constructed as explained in the text, i.e. $MS^{actual}_{j,t,t+1} = \left[Stock^{actual}_{j,t+1} - Stock^{actual}_{j,t}\right] + \delta_j \cdot Stock^{actual}_{j,t}$ where estimates for δ_j are taken from the BEA (2003). CHNS data 1989 to 2009.

(about \$800,000 at the current exchange rate) plus all state-owned firms in manufacturing. The raw data consists of over 150,000 firms in 1998 and grows to over 300'000 firms in 2007. The ASIP covers a wide range of information about the firm's balance sheet, cash-flow and ownership which provides us with a rich set of control variables. This data set has been used extensively in the recent literature.[10]

We estimate total factor productivity (TFP) at the firm-level using data on value-added, the stock of fixed assets, intermediate inputs and employment applying the estimation procedure suggested by Levinsohn and Petrin (2003) to account for the endogeneity of factor input choices.[11] We take TFP as a proxy for the investment in innovation.[12] We check the robustness of our results by using labor productivity as a second measure of innovation activities. This is sometimes preferred to TFP in the literature, due to its superior stability (see also Crépon *et al.*, 1998). The most natural measure of innovation however, would be R&D expenditure. But unfortunately, we cannot use this measure as it is only available for the years 2005 to 2007.

We link each durable good observed in the CHNS to the four digit manufacturing industry producing it as a final household consumption good according to the NBS (2008) description of the Chinese Industry Classification (CIC) system. A limitation of this approach is that it neglects those industries which produce the durable goods as equipment or intermediate inputs (as opposed to final goods) for other industries – this is however quantitatively not very important for the durable goods we consider. We collapse the 22 categories of durable goods available from the CHNS into 16 manufacturing industries, as in some cases different durable goods are produced by firms belonging in the same four-digit manufacturing industry.[13] Following Brandt et *al.* (2011) we exclude all firms with less then 8 employees and those with negative values of value-added and capital stock.[14] Additionally, as noted by Feenstra *et al.* (2011), the NBS data are fairly noisy due to mis-reporting and other sources of measurement error. Since measurement error is likely to be larger among very small (e.g. family-managed) firms, which do not set up a formal

[10]A detailed description of the data set can be found in Brandt *et al.* (2011). Other recent papers include, for instance, Feenstra *et al.* (2011) and Hsieh and Klenow (2009).

[11]The estimation of total factor productivity is explained in greater detail in Appendix D.1.2.

[12]Using TFP as a proxy for innovative investments is common in the literature. See among others, Crépon *et al.* (1998) or Acemoglu *et al.* (2010).

[13]Since color TVs and DVD players are produced by the same four-digit manufacturing industries, we created a new ownership variable for home video appliances which is simply the cumulative ownership of those two goods irrespectively whether this is a color TV or a DVD player. We proceed in a similar fashion in the case of the kitchen appliance industry as the cumulative of microwaves, rice cookers and pressure cookers and in the case of the cycle industry being the cumulative of bicycles and tricycles. The exact list of durable goods and matched industries can be found in Table D.3 in the data appendix.

[14]We also employ their procedure to link restructured firms over time, cf. the online appendix of Brandt *et al.* (2011) for more details.

accounting system, we exclude the smallest 10% of firms in terms of value-added (on a yearly basis).[15] We end up with a final sample of 30'883 firm observations in 16 durable good industries over the years 1998–2007.

4.3 Empirical Strategy

4.3.1 Econometric Model

To study the effect of market size on innovation we consider the following regression model

$$\ln Y_{i,j,t} = \alpha \left(\ln MS^{actual}_{j,t,t+4}\right) + \mathbf{X}'_{i,j,t}\beta + \psi HHI_{j,t} + \eta_j + \lambda_t + \epsilon_{i,j,t},$$

where i denotes a firm, j an industry (durable good) and t the time. The main goal is to estimate the effect of the future market size at the industry level, $MS^{actual}_{j,t,t+4}$, on the firm-level measure of innovation activity, $Y_{i,j,t}$. $MS^{actual}_{j,t,t+4}$ measures the annual average change in the total number of items of a durable good j between t and $t+4$ adjusted for depreciation, as discussed above. The five-year window benchmark is similar as in Acemoglu and Linn (2004), as this is a plausible time horizon to determine firms' investments in innovation. Our main outcome variable is TFP, a proxy for the firm-level investment in technology adoption. We perform robustness analysis using alternative proxies for innovation such as labor productivity, as well as alternative windows for future market size.[16]

In all specifications, we include industry fixed effects, η_j, to account for industry-specific innovation intensities (e.g., the car industry is inherently more technology-intensive than the bicycle industry). Time fixed effects, λ_t, absorb aggregate shocks (e.g., business cycle fluctuations, China joining the WTO, etc.). The vector $\mathbf{X}_{i,j,t}$ controls for unobserved firm-level heterogeneity to ensure that estimates are not biased by omitted determinants of investment in innovation.[17] First, we control for the firm size using the log number of workers as suggested in the literature. This is important since firm size could be a determinant of its propensity to invest in innovation. Second, we control for the ownership structure of firms that can be important to determine firms' financial structure and innovativeness.[18] Specifically, we take privately owned firms as the reference group

[15] Alternatively, Feenstra *et al.* (2011) suggest to exclude firms for which some key accounting identities are not matched in the data. This results in a quite rigorous filtering, however, which would substantially shrink our sample of durable good firms.

[16] Depending on the length of the time window, we have to exclude certain industries from the analysis, e.g. since satellite dish ownership is only available from 2006 onwards, we have to exclude this industry in our baseline analysis with the five-year time window.

[17] See Crépon *et al.* (1998) and Mairesse and Mohnen (2010) for a review of firm-level innovation determinants.

[18] See for example Song *et al.* (2011).

and introduce three dummy variables for whether a firm is foreign, state or collective owned. Third, we add a dummy for firms that are older than six years (the median in our sample) in order to control for the age of firms.[19] Further, we include a dummy for firms located in coastal provinces, worrying that firms in the booming coastal regions might be overrepresented in some sectors. Finally, to control for different intensities of market competition across sectors, we introduce the Hirschmann-Herfindahl index, which is defined as the sum of squared market shares of all firms within the sector.[20] Summary statistics on all variables are listed in Table D.4.

The coefficient of interest, α, captures the effect of future market size on a firm's investment in technology. The theory of directed technical change outlined in the introduction predicts that α should be positive. As both our dependent variable and market size are in logs, the coefficient can be interpreted as an elasticity. We now discuss how we address a number of econometric concerns.

4.3.2 Endogeneity and Potential Market Size

The most important econometric issue is the potential endogeneity of the market size measure. Firms' investments in technology adoption can influence the future stream of durable good purchases by affecting the prices or the quality of durable goods. For instance, process innovation reduces production costs, whereas product innovation makes available better varieties for which consumers are willing to pay more. Through these channels, a higher intensity of innovation in an industry may increase the industry's future market size. Due to the endogeneity problem, OLS regressions may yield inconsistent estimates of the parameter α. To address this problem, we instrument $MS^{actual}_{j,t,t+4}$ with a measure of potential market size, $MS^{potential}_{j,t,t+4}$ which is independent of supply shocks affecting the prices or the quality of durable goods. The identification strategy is in close spirit to the ony employed by Acemoglu and Linn (2004). They use demographic variables to predict the evolution of market size for different drugs, taking into account the usage pattern across age groups in the population. Intuitively, a fast-aging population implies that the market for drugs used to treat patients suffering from the Alzheimer syndrome grows faster than that for drugs used to treat child obesity. Their demography-based measure of potential market size is exogenous to innovative investments, and is therefore a valid

[19] Arnold and Hussinger (2005) for example argue that due to possible correlation between size and age of a firm employing a dummy instead of the absolute age seems to be the correct estimation approach.

[20] Studies that specifically employ the HHI are for example Cotterill (1986), Farrell and Shapiro (1990) and Farrell and Shapiro (1990). We define the HHI for industry j at time t as the sum of squared market shares (in value-added) of all firms operating within this sector at time t. Since we calculate market shares in percentage terms, (between 0 and 100), the HHI lies in the range between 0 and 10 000. We are aware of the fact that the border of markets is less clear for globally operating firms. However, we consider the HHI as the first best measure to capture market competition within the firm's primary (home) market.

instrument. Similarly, in our paper we assume that the market size of each durable good depends on the evolution of income growth and the income distribution, given the diffusion curve associated with each durable good. In particular, we assume that households in different income brackets purchase each durable good with a given probability that we estimate. Then, we construct a measure of *potential* market size for each durable good that depends only on macroeconomic variables (e.g. the growth of household income) and not on supply-driven shocks. Under the assumption that macroeconomic changes are exogenous to firms (and industries) investing in new technologies, market potential is a valid instrument for the actual market size. Note that the exclusion restriction would be violated if the innovative investments of firms producing a particular good could affect the future aggregate economic growth (or income distribution) in China. However, this is unlikely to be the case since we focus on narrowly defined industries producing small shares of the total income of China.[21]

More formally, we start from breaking down the Chinese population into four groups using fixed income thresholds in constant 2009 Yuan.[22] Figure 4.3 shows the evolution of the population shares of the four income groups over the survey period. The population share of the two poorer groups falls dramatically over time, especially between 2000 (85 %) and 2009 (47%). Conversely, the share of high income households increases from almost zero in 1997 to 20% in 2009. Together, the two upper income groups account to 52% in 2009.

Next, we construct the usage intensities, $u_{j,g,t}$, by estimating the number of items per capita of each durable good j owned by agents in income group g at time t. Table D.2 in Appendix D.1.3 presents these usage profiles for the year 2009 in our dataset. As expected, the usage profiles are upward sloping for all durable goods. Yet, there are considerable differences between durable goods. Electric fans, for instance, feature the largest increase in usage at the lower end of the income distribution whereas the usage of cars increases the most as an individual switches from the second highest to the highest group. These differences across usage patterns are the crux of our identification.

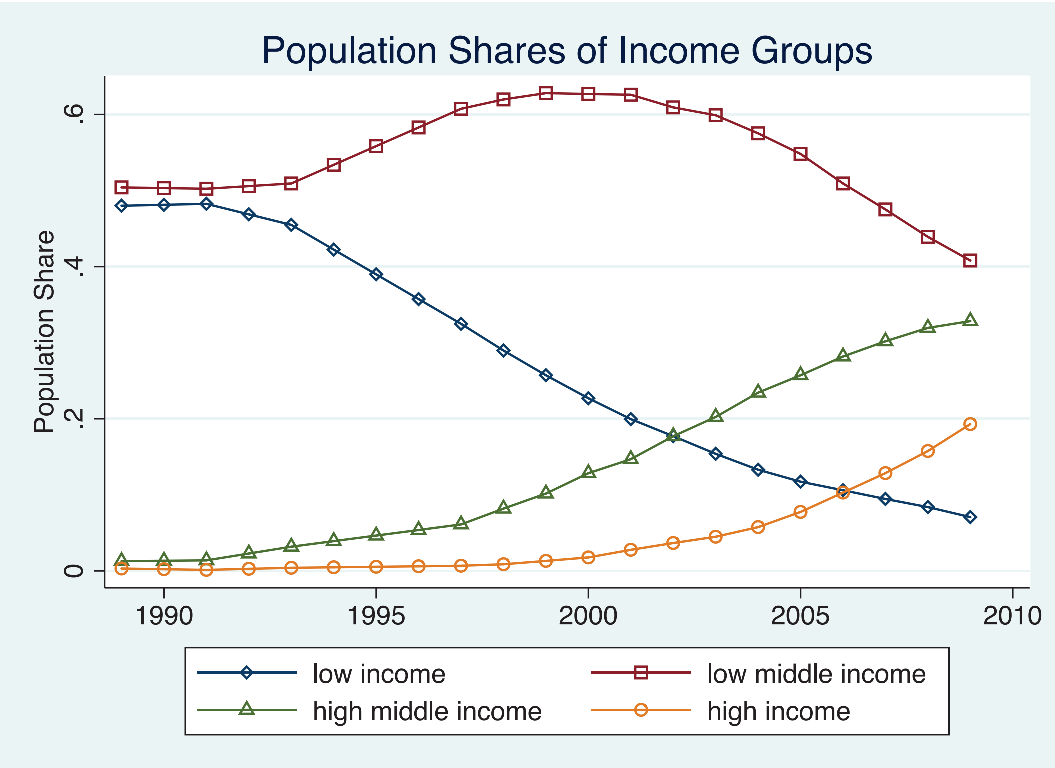
Finally, we construct our measure of potential market size as

---

[21] Also, although investments in innovation are correlated across industries, recall that we control for time dummies in our regressions, so the identification comes from deviations from common trends in TFP.

[22] Households are assigned to four income groups according to their household income per capita following a classification of the WB (2009) Atlas method that assigns countries into 4 groups according to their GNI per capita in 2009. With some adjustments to account for small sampling of the high income group, the groups are: low income (below 2'150 Yuan), lower middle income (2'150 - 8'514 Yuan), upper middle income (8'515 - 16'499 Yuan), high income (16'500 Yuan or more). In constant 2009 \$, this corresponds roughly to: low income, US \$ 2'149, low middle income, US \$ 2'150 -US \$ 4'167, high middle income, US \$ 4'168 - US \$ 8'075, high income, US \$ 8'076 or more. See Appendix D.1.1 details.

Figure 4.3: Evolution of Income Groups According to WB Classification



Notes: CHNS data 1989 to 2009. Households classified into four income groups according to their household income per capita in constant 2009 Yuan: low income (below 2'150 Yuan), lower middle income (2'150 - 8'514 Yuan), upper middle income (8'515 - 16'499 Yuan), high income (16'500 Yuan or more).

$$MS_{j,t,t+1}^{potential} = \left(Stock_{j,t+1}^{potential} - Stock_{j,t}^{potential}\right) + \delta_j \cdot Stock_{j,t}^{potential},$$

where

$$Stock_{j,t}^{potential} = \sum_g \overline{u}_{j,g} \cdot i_{g,t},$$

and $i_{g,t}$ is the number of people in income group g in year t and $\overline{u}_{j,g} = u_{j,g,t=2009}$ is the number of item of durable good j owned per head in income group g in the year 2009.[23] Our measure exploits the fact that there are significant differences in the ownership of durable goods across income groups. As the economy grows, more households enter higher income groups and start purchasing durable goods. This process affects asymmetrically the demand of different durable goods. As Table D.2 shows, durable goods whose diffusion increases the most across low income groups (such as electric fans or motorcycles), diffuse faster at an earlier stage of development. In contrast, for goods such as cars, the diffusion is fastest as more households climb up into the highest income group. Note that there are differences between $MS_{j,t,t+1}^{potential}$ and $MS_{j,t,t+1}^{actual}$. Part of these differences reflect changes (typically, increases) in the usage intensities that apply to all income groups. Beerli (2010), shows that a large part of these is explained by falls in prices.[24] Price-driven changes in demand, in turn, are likely to be related to supply-side shocks, e.g. technical progress reducing the production cost. Our measure of potential market size abstracts from such changes and is therefore immune from supply-side shocks. In other words, changes in prices and quality of durable goods which may result from investments in technology adoption, cannot cause over-time variation in $MS_{j,t,t+1}^{potential}$.[25] In fact, Figure D.1 in Appendix D.1.4 reveals that income-specific usage rates are indeed changing due to differential price dynamics. Moreover, the variation across industries shows the differential speed of technological progress across industries.

---

[23]Note that the choice among different CHNS waves as base-year is to some extent arbitrary. Because the 2009 wave of the CHNS has the richest coverage of durable goods and the highest income group is sampled more accurately than in earlier years, we pick 2009 as our best choice of a base-year. See Appendix D.1.1 for a detailed discussion.

[24]An example is color TVs. Beerli (2010) shows that the rise in income levels can only explain about one third of the total increase in color TV ownership for an average household between 1989 and 2006.

[25]We are particularly concerned that innovation activities of firms in year t may affect future usage intensities, i.e. $u_{j,g,t+k}$ with $k > 0$, and through this the expected market size in upcoming years, $MS_{j,t,t+k}^{actual}$. Thus, a less conservative notion of potential market size would allow to use lagged usage intensities for each given year. Yet, as innovation activities of firms show considerable serial correlation, we take the most conservative approach possible and fix usage intensities to one specific year.

4.3.3 Omitted Variables

The estimate could also suffer from an omitted variable bias. In this respect, we address two important specific issues. First, while we focus on the expansion of the domestic durable good market, Chinese firms also engage in a significant export activity. Thus, investment in new technologies may be driven by foreign demand as well. We address this issue in two ways: first, we include a dummy capturing whether a firm is engaged in export activities. Second, to analyze whether exporting firms are significantly different from domestic-serving firms, we additionally include an interaction term between our market size measure and the export indicator.
Another potential source of bias could be global technology shocks which affect differentially the propensity of firms to innovate in different industries. An example could be the rise of automation technology (compare e.g. Autor *et al.*, 2003). To address this concern, we control for an industry-specific measure of worldwide technology potential reported by Swiss firms.

4.4 Results

4.4.1 OLS and IV Regressions

We start by estimating a set of standard OLS regressions, whose results are reported in Table 4.1. All regressions include time and industry fixed effects. Standard errors are clustered at the industry-year level. Namely, we allow for correlation between error terms related to observations belonging to the same industry in each given year.[26]

Table 4.1 reports the results. We do not report the estimated coefficients for the full set of control variables, which are deferred to the Appendix (see Table D.8 in Appendix D.2). Column (1) yields the estimate of α in the baseline OLS regression without controls. The coefficient is positive and highly significant. Increasing the future market size by one percent raises firms' TFP by 0.19%. However, part of the effect could be spuriously driven by omitted time-varying firm characteristics. We then control for a large number of firm-level variables including size, ownership, age, and location.[27] We also control for the Hirschmann-Herfindahl index for market competition at the industry level. Controlling

[26]We also consider an alternative clustering strategy allowing for correlation of the error terms at the firm-level. Clustering at the industry-year level turns out to be generally more demanding. An even more demanding strategy would be to cluster standard errors at the industry level. However, this is not possible with our data, since the number of clusters would in this case be too small (see Angrist and Pischke, 2009 for a discussion of the problems arising with too few clusters). Following Angrist and Pischke (2009), we check the validity of our results by collapsing observations on the industry level.

[27]See Crépon *et al.* (1998) and Mairesse and Mohnen (2010) for a review of firm-level innovation determinants.

for these firm and industry characteristics causes a reduction in the size of the estimated coefficient, which falls to 0.6% turning statistically insignificant, see column (2) of Table 4.1. Clustering at the firm-level reduces the estimated standard error but the coefficient of interest remains insignificant (see column (3)).

Next, we run two-stage least squares (2SLS) regressions to account for the endogeneity of the actual market size measure. We use our measure of "potential market size" as an instrument for the actual market size. As explained in Section 4.3.2, potential market size is exclusively driven by future changes in the income distribution. This measure is orthogonal to price or quality changes that could affect changes in ownership patterns and cause an endogeneity problem. Formally, for this to be a valid instrument, it must be correlated with the actual market size and be uncorrelated with the error term.

The results of the 2SLS regressions are reported in columns (4)-(6) of Table 4.1. The effect of market size on firms' TFP is larger and more precisely estimated than in the OLS specification. Column (4) repeats the regression of column (1), where we control only for industry and time fixed effects. The estimated coefficient is positive and highly significant. Controlling for the firm- and industry level characteristics listed above yields a lower coefficient. However, this remains large and highly significant. The estimate in column (5) - the analogue of the OLS regression in column (2) - implies that a one percent exogenous increase in market size leads to an increase in TFP of 0.27%. This is a large effect (more than four times as large as the OLS estimate), suggesting the importance of profit incentives as a driver of firms' innovation activities. Column (6) completes the picture by clustering the standard errors at the firm-level. This yields an even higher p-value of the estimated coefficient.[28]

Table 4.2 presents the results of the first stage regressions. Columns (1)-(2) show the results corresponding to columns (4)-(5) in Table 4.1. Potential market size is significantly correlated with the actual measure of market size and suggests that a one percent change in potential market size (driven only by income changes) leads to a change in actual market size by nearly 2%. The last row of Table 4.2 shows that the F-statistic of the excluded instrument is well above the conventional threshold of 10.[29] Column (3) repeats the regression of column (2) clustering standard errors at the firm-level.

[28]The standard error of the estimated coefficient blows up if we cluster residuals at the industry level, rendering the estimated coefficient insignificant. However, as discussed above, this approach is problematic, and we do not emphasize it.

[29]Compare e.g. Staiger and Stock (1997) for details on the critical F-statistic that reveals a weak instrument problem.

Table 4.1: Effect of Market Size on LN TFP

Dep. Variable	$\ln TFP_{i,j,t}$					
Mean	5.137	5.137	5.137	5.137	5.137	5.137
St.Dev.	1.161	1.161	1.161	1.161	1.161	1.161
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln MS^{actual}_{j,t,t+4}$	0.188	0.0628	0.0628	0.549	0.272	0.272
	[0.0813]**	[0.0525]	[0.0395]	[0.185]***	[0.132]**	[0.0828]***
Firm Controls	No	Yes	Yes	No	Yes	Yes
Method	OLS	OLS	OLS	2SLS	2SLS	2SLS
Observations	20,167	20,160	20,160	20,167	20,160	20,160
R^2	0.111	0.278	0.278	0.106	0.277	0.277
Clustering	Industry x Year	Industry x Year	Firm	Industry x Year	Industry x Year	Firm
No of Clusters	111	111	7662	111	111	7662
F-Stats				27.68	26.70	1480

Notes: *** p<0.01, ** p<0.05, * p<0.1 denote significance on the 10%, 5% and 1% level, respectively. Observations below the 10 percentile of value-added each year are excluded. All columns include year and industry fixed effects. Columns (2)-(3) and (5)-(6) include a set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). $\ln MS^{actual}_{j,t,t+4}$ is instrumented with $\ln MS^{potential}_{j,t,t+4}$.

Table 4.2: First Stage Regression

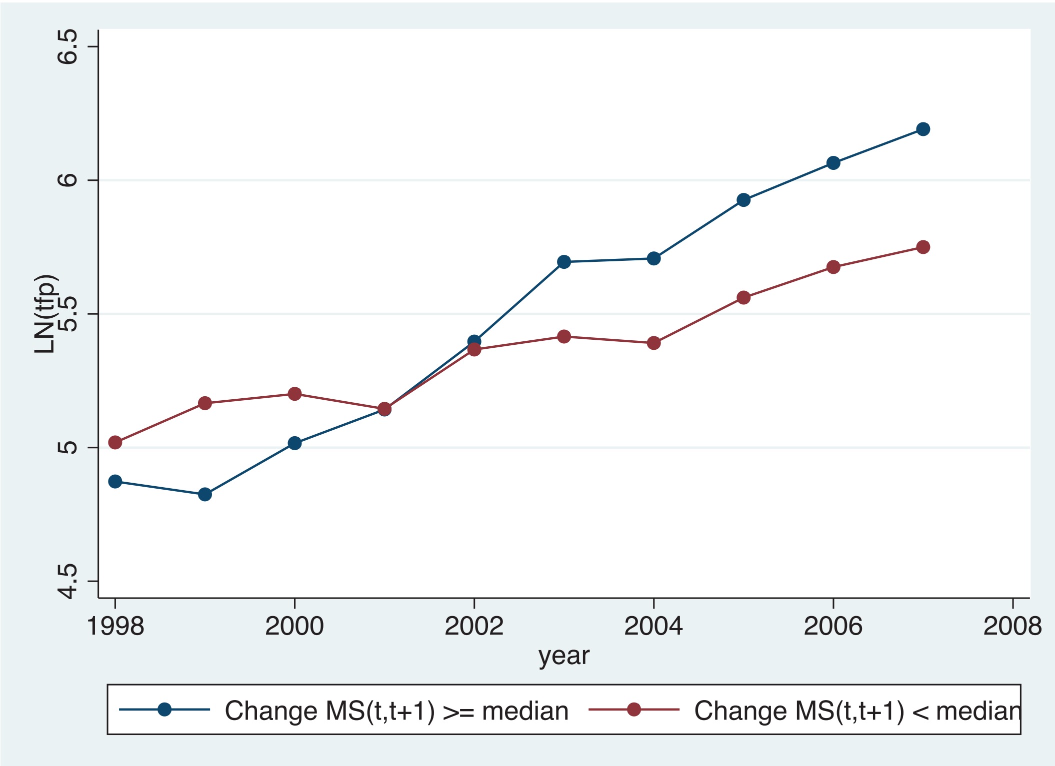
Dep. Variable	$\ln MS^{actual}_{j,t,t+4}$		
	(1)	(2)	(3)
$\ln MS^{potential}_{j,t,t+4}$	1.967	1.955	1.955
	[0.374]***	[0.378]***	[0.0508]***
Firm controls	No	Yes	Yes
Observations	20,167	20,160	20,160
R^2	0.244	0.239	0.239
Clustering	Industry x Year	Industry x Year	Firm
No of Clusters	111	111	7662
F-Stats	27.68	26.70	1480

Notes: *** p<0.01, ** p<0.05, * p<0.1 denote significance on the 10%, 5% and 1% level, respectively. Observations below the 10 percentile of value-added each year are excluded. All columns include year and industry fixed effects. Columns (2)-(3) include a set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). The reported R^2 reported equals the partial R^2.

Finally, Figure 4.4 summarizes our empirical findings by a convenient visualization. We split our data sample at the median value of the change in potential market size between 1998 and 2007.[30] Then we plot the evolution of log productivity broken down by above - and below median industries. Since we empirically stress the importance of the market size effect for firms' innovation behavior, we expect TFP to increase faster for firms within industries that are subject to a positive demand shock over the sample period. The Figure shows that this is indeed the case. Productivity increased by 1.3 log points in industries above the median change in market size between 1998 and 2007 whereas industries below increased by 0.7 log points.

[30]We calculate the median value of the change in one-year potential market size between 1998 and 2007. For each industry, this value is $\Delta MS^{potential}_{j,1998,2007} = \ln MS^{potential}_{j,2007,2008} - \ln MS^{potential}_{j,1998,1999}$. Looking at the change in potential market size ensures that we ignore level differences of market size between industries, as we do later in the regression when we use industry fixed effects.

Figure 4.4: Evolution of log productivity in industries above and below the median change in potential market size between 1998 and 2007



Notes: All ASIP data 1998 to 2007. Industries allocated to groups according to the change in market size between 1998 and 2007, i.e. $\Delta MS^{potential}_{j,1998,2007} = \ln MS^{potential}_{j,2007,2008} - \ln MS^{potential}_{j,1998,1999}$. Industries above the median, $\Delta MS^{potential}_{j,1998,2007} >= \Delta\overline{MS}^{potential}_{1998,2007}$, are camera, air condition, computer, car, radio, refrigerator, telephone and kitchen appliances. Industries below the median, $\Delta MS^{potential}_{j,1998,2007} < \Delta\overline{MS}^{potential}_{1998,2007}$, are washing machine, sewing machine, home video appliances, cycles, electric fan, motorcycle, satellite dish. The mean value of $\ln TFP_{j,t}$ within groups was calculated using each industry's value-added as weight. The cellphone industry is omitted from this figure as it is only covered in the ASIP after 2003.

4.5 Robustness

4.5.1 Trimming

In the regressions of Table 4.1, we use a trimmed sample excluding the smallest 10% of the firms in terms of value-added on a yearly basis. The exclusion of small firms is motivated by the fact that the TFP estimates of small firms are very noisy. In this section we show the sensitivity of the results with respect to alternative trimming thresholds. Column (3) of Table 4.3 shows the baseline 2SLS estimation (column (5) in Table 4.1), for reference, while columns (1)-(2) and (4)-(5) show the results of the corresponding regressions under different thresholds.[31] The coefficient of interest becomes larger and more precisely estimated the more we trim. No trimming at all yields a coefficient of 0.17, statistically insignificant (see column (1) of Table 4.3). Trimming 5% of the observations yields a coefficient of 0.23 (compared with 0.27 in the benchmark case) which is significant at the 10 percent level. Restricting the dataset further by trimming 25% and 50% respectively, yields even larger coefficients. Note also that the standard error of TFP decreases the more we trim the sample, suggesting that measurement error may be more severe among small firms.

Table 4.3: Robustness Analysis: Trimming

Dep. Variable	$\ln TFP_{i,j,t}$				
Mean	4.894	5.044	5.137	5.370	5.783
St.Dev.	1.395	1.215	1.161	1.085	1.007
	(1)	(2)	(3)	(4)	(5)
$\ln MS^{actual}_{j,t,t+4}$	0.167	0.231	0.272	0.382	0.485
	[0.131]	[0.136]*	[0.132]**	[0.136]***	[0.137]***
Method	2SLS	2SLS	2SLS	2SLS	2SLS
Observations	22,328	21,241	20,160	16,900	11,412
R^2	0.303	0.287	0.277	0.249	0.212
Trimming	0%	5%	10%	25%	50%
F-Stats	27.32	26.95	26.70	27.27	28.41

Notes: *** p<0.01, ** p<0.05, * p<0.1 denote significance on the 10%, 5% and 1% level, respectively. Robust standard errors (clustered on the industry-year level jt) are given in parentheses. All columns include year and industry fixed effects as well as a set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). $\ln MS^{actual}_{j,t,t+4}$ is instrumented with $\ln MS^{potential}_{j,t,t+4}$.

4.5.2 Omitted Variables

A natural concern with our investigation is China's export market. One might suspect the export market to be a key driver of investments in an export-oriented economy like China. As Table D.4 and Figure D.2 show, 49% of all firms in the durable good industries

[31] The corresponding first stage regressions are found in Appendix D.2.

considered in our study engage in export activities. The export exposure varies considerably across industries. For instance, the average fraction of sales going to foreign markets is high for camera and radio manufacturers (60% and 58%, respectively), while it is fairly low for car and refrigerator manufacturers (2% and 13%, respectively).[32] In Table 4.4 we show that our previous results are robust to controlling for export behavior.[33] Column (1) is the same as column (5) in Table 4.1. In column (2), we include among the regressors an indicator for whether a firm has positive export sales. As expected, we find that exporters are on average more productive than non-exporters; yet, the inclusion of this dummy leaves the coefficient of interested practically unchanged. In column (3), we add an interaction term between the exporter dummy and the market size measure to investigate whether the effect of the domestic market is systematically different between exporters and non-exporters. The coefficient of the interaction term shows that the effect of the domestic market on innovation is stronger for non-exporters than for exporters. The difference is statistically significant. Alternatively, we estimate the market size effect separately for exporters and non-exporting firms. Again, we find the coefficient of market size to be highly significant (and substantially larger) for non-exporting firms only, while exporting firms show no effect (see Table D.9 in Appendix D.2). Both results are consistent with the view that the expansion of the domestic market size is less important for globally active firms.[34]

Another concern is that global technology shocks could affect the innovation behavior of firms and be correlated with the dynamic of the domestic market.[35] To control for global technology shocks, we include a survey measure of technological opportunities constructed according to the assessment of Swiss firms as reported by the KOF Innovation Survey (2012). In this survey, firms are asked to assess the worldwide availability of technological know-how in private and public hands which could be used to generate marketable new products.[36] Swiss firms have traditionally occupied a strong position in international science and technology activities (see OECD, 2013; Arvanities *et al.*, 2010). Thus, the

[32]Detailed descriptive statistics on the industry level are found in Tables D.5 - D.7 in Appendix D.1.3.

[33]The corresponding first stage regressions are found in Appendix D.2.

[34]In fact, Figure D.2 shows that the distribution of firms ranked by their exportshare relative to total sales is highly bimodal. Thus, firms seem to serve either only the domestic or exclusively the foreign market, which explains the insignificance of the market size effect for exporters.

[35]In a recent survey of the literature, Draca *et al.* (2006) show that there was a considerable impact of ICT availability on productivity. Additionally, Bloom *et al.* (2012) show the effect of IT on productivity was differential even within industries depending on whether firms were US- or non-US-multinationals.

[36]The KOF Innovation Survey (KOF, 2012) covers a representative sample of Swiss firms in the manufacturing, construction and service sector on a three yearly basis since 1990. To the best of our knowledge, the KOF Innovation Survey is the only publicly available innovation survey which can be used on a highly disaggregate sector level (four digits). Additionally, we check for robustness of this measure using standard innovation measures such as R&D spending, the number of patents and new product outputs share on the same industry level.

information reported by Swiss firms reflect to a considerable degree these global trends in technology. We match this technology potential measure to our durable good industries on a fine grained three or two digit industry level. This variable shows considerable variation across time and over industries (see Figure D.3).[37] As can be seen in column (4), controlling for global technology shocks does not affect significantly the market size effect on TFP. Controlling for both technology shocks and exports (column (5)) has no significant effect on the coefficient of market size either.

Table 4.4: Robustness Analysis: Controlling for Exports and Technology Supply Shocks

Dep. Variable	$\ln TFP_{i,j,t}$				
Mean	5.137	5.138	5.138	5.137	5.138
St. Dev.	1.161	1.160	1.160	1.161	1.160
	(1)	(2)	(3)	(4)	(5)
$\ln MS^{actual}_{j,t,t+4}$	0.272	0.274	0.288	0.265	0.267
	[0.132]**	[0.133]**	[0.124]**	[0.135]**	[0.136]**
$\ln MS^{actual}_{j,t,t+4} \times 1(EXP_{i,j,t} > 0)$			-0.152		
			[0.0286]***		
$1(EXP_{i,j,t} > 0)$		0.0539	2.635		0.0540
		[0.0274]**	[0.486]***		[0.0274]**
$TECHPOT_{j,t}$				-0.00541	-0.00558
				[0.0236]	[0.0240]
Method	2SLS	2SLS	2SLS	2SLS	2SLS
Observations	20,160	20,147	20,147	20,160	20,147
R^2	0.277	0.277	0.280	0.277	0.277
F-Stats	26.70	26.88		21.17	21.31
F-Stats1			40.31		
F-Stats2			839.5		

Notes: *** p<0.01, ** p<0.05, * p<0.1 denote significance on the 10%, 5% and 1% level, respectively. Robust standard errors (clustered on the industry-year level jt) are given in parentheses. Observations below the 10 percentile of value-added each year are excluded. All columns include year and industry fixed effects as well as a set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). $1(EXP_{i,j,t} > 0)$ is one if a firm has positive export sales. $\ln MS^{actual}_{j,t,t+4}$ is instrumented with $\ln MS^{potential}_{j,t,t+4}$ and $\ln MS^{actual}_{j,t,t+4} \times 1(EXP_{i,j,t} > 0)$ with $\ln MS^{potential}_{j,t,t+4} \times 1(EXP_{i,j,t} > 0)$. $TECHPOT_{j,t}$ is the world wide technology potential assessed by Swiss firms in the KOF Innovation Survey.

4.5.3 Using Labor Productivity instead of TFP

In this section, we consider (the log of) labor productivity as an alternative dependent variable. While labor productivity may increase due to capital deepening, rather than investment in innovation, it has the advantage of being a less noisy measure than TFP. Labor productivity is computed as the value-added per employee. Table 4.5 displays the results.[38] All regressions include the full set of control variables used in Table 4.1.

[37]To maximize accuracy and cross-industry variation, we use three digit industry levels whenever the data allows us to do so. If an industry is not available in the Swiss firm sample we take the next higher industry classification. This allows us to get variation over eight different durable good industries.

[38]The corresponding first stage regressions are found in Appendix D.2.

Column (1) shows the result of the OLS regression - the coefficient of market size is now positive and highly significant, contrary to Table 4.1. Column (2) shows our preferred specification. The effect is again positive and significant. An increase in market size by one percent yields an increase of 0.4% in firm's labor productivity. Again, the 2SLS estimates are larger than the corresponding OLS estimate. Column (3) shows the results when standard errors are clustered at the firm-level. Finally, column (4) of Table 4.5 shows that results are robust to the inclusion of the additional controls for export behavior of firms and the technology potential measure to account for supply-side drivers (as discussed in Section 4.5.2).

Table 4.5: IV Regression on LN Laborproductivity

Dep. Variable	$\ln Laborproductivity_{i,j,t}$			
Mean	3.932	3.932	3.932	3.933
St.Dev.	1.148	1.148	1.148	1.148
	(1)	(2)	(3)	(4)
$\ln MS^{actual}_{j,t,t+4}$	0.178	0.401	0.401	0.424
	[0.0696]**	[0.160]**	[0.0858]***	[0.171]**
$1(EXP_{i,j,t} > 0)$	No	No	No	Yes
$TECHPOT_{j,t}$	No	No	No	Yes
Method	OLS	2SLS	2SLS	2SLS
Observations	20,160	20,160	20,160	20,147
R^2	0.178	0.176	0.176	0.177
Clustering	Industry x Year	Inustry x Year	Firm	Industry x Year
No of Clusters	111	111	7662	111
F-Stats		26.70	1480	21.31

Notes: *** p<0.01, ** p<0.05, * p<0.1 denote significance on the 10%, 5% and 1% level, respectively. Observations below the 10 percentile of value-added each year are excluded. All columns include year and industry fixed effects and a set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). Column (4) in addition introduces a dummy for positive exports, $1(EXP_{i,j,t} > 0)$ and the supply side control, $TECHPOT_{j,t}$. $\ln MS^{actual}_{j,t,t+4}$ is instrumented with $\ln MS^{potential}_{j,t,t+4}$.

4.5.4 Regressions on the Industry Level

Since our innovation measure comes from the firm-level dataset but the market size effect is identified at the industry level, there may be a risk of underestimating the standard errors. Although we cluster standard errors at the industry-time level, a remaining concern is that observations may be correlated at the industry level over different periods. While clustering at the industry level would resolve this issue, this avenue is not possible due to an insufficient number of clusters. As a way to mitigate concerns, we check if the results are robust to collapsing all firm-level observations at the industry level and re-run our baseline regressions using a weighted least squares approach, using the number of firms within each industry as weights, as suggested by Angrist and Pischke (2009). In addition, we control for heteroscedasticity among error terms and report robust standard errors. Table 4.6 displays similar regressions shown in Table 4.1 using either TFP (columns (1)-(3)) or labor productivity (columns (4)-(6)) as the dependent variable.[39] All specifications include the full set of industry and time fixed effects and the set of control variables of size, age, region, market competition, ownership structures. Columns (3) and (6) additionally control for export behavior and technology potential as supply side driver (see above). In particular, the new set of controls is defined as the (unweighted) mean over all firm-level variables within one industry and each year including the mean of dummies such as ownership.[40]

The results are similar to those in Table 4.1. In our preferred 2SLS specification with the full set of controls (see columns (3) and (6) of Table 4.6), an increase of industry's market size by one percent translates into an increase in TFP of about 0.68% and into an increase in labor productivity of about 0.7%.[41] These results are reassuring and provide additional credibility to the firm-level analysis.

[39] In particular, we focus on the specifications that include the full set of firm-level controls.

[40] Corresponding first stage regressions are found in Table D.15 in Appendix D.2.

[41] Note that the F-statistics in columns (2) and (5) are below the conventional level of 10. Thus, these regressions are subject to a mild weak instrument problem and we prefer the specification with all control variables including export behavior and technology potential.

Table 4.6: Effect of Market Size on LN TFP

Dep. Variable	$\ln TFP_{i,j,t}$			$\ln Laborproductivity_{i,j,t}$		
Mean	5.772	5.772	5.772	4.544	4.544	4.544
St.Dev.	0.597	0.597	0.597	0.641	0.641	0.641
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln MS^{actual}_{j,t,t+4}$	0.184	0.643	0.678	0.400	0.579	0.709
	[0.0720]**	[0.238]***	[0.205]***	[0.0914]***	[0.255]**	[0.200]***
Method	OLS	2SLS	2SLS	OLS	2SLS	2SLS
Observations	111	111	111	111	111	111
R^2	0.961	0.942	0.939	0.959	0.956	0.952
F-Stats		7.459	15.25		7.459	15.25

Notes: *** p<0.01, ** p<0.05, * p<0.1 denote significance on the 10%, 5% and 1% level, respectively. Robust standard errors are given in parentheses. Observations below the 10 percentile of value-added each year are excluded. All columns include year and industry fixed effects as well as the simple industry mean of the set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). Column (3), (6) in addition introduce a dummy for positive exports, $1(EXP_{i,j,t} > 0)$ and the supply side control, $TECHPOT_{j,t}$. $\ln MS^{actual}_{j,t,t+4}$ is instrumented with $\ln MS^{potential}_{j,t,t+4}$. Regressions are weighted by the number of firms within a sector.

4.6 Conclusion

Much of the previous literature studying determinants of the spectacular growth performance of the Chinese economy has focused on supply- and technology-factors, while the role of demand forces is still poorly understood. This paper focuses on firm's expectations about future market size as a potentially important channel that contributes to our understanding of technical progress in the Chinese manufacturing sector. The basic source of variation for potential market size comes from Chinese growth and its huge (and predictable) impact on the Chinese income distribution. In 1990, 99 percent of Chinese consumers had an income lower than 8500 Yuan (at constant 2009 prices) and were low- or lower-middle income households according to World Bank Classification. By the year 2009, this fraction had fallen to 50 percent. The associated change in the Chinese income distribution did not affect industries equally. To the extent that the Engel-curves for the industry's various products is non-linear, industries are affected differentially. It is this source of variation that underlies our identification strategy.

To establish an empirical link between expected market size and technical progress, we combine household-expenditure data from Chinese Health and Nutrition Survey (CHNS) and firm-level data from the Annual Survey of Industrial Production (ASIP). Looking at 16 industries covering a substantial share of household expenditures for consumer durables, CHNS data allows us to construct product-specific Engel-curves for the 16 consumer durables. Combining these income-driven changes in consumer behavior with information on the income distribution (income-class specific population shares) allows us to estimate a measure of expected market size, whose evolution over time is entirely driven by income growth. Using firm-specific productivity data estimated from ASIP data, we ask how firm performance is affected by expected market size. Our findings suggest that demand effects are quantitatively important: a one percent increase in expected market size increases firm-specific TFP by 0.27% and firm-specific labor productivity by 0.42%. Firms in industries with a large expected local market are significantly more productive today, and show higher levels of other measures of innovative activity. We think that, in the future, the role of demand forces may become even stronger as a driver of Chinese growth than they were in in the recent past. China's share of private consumption in total GDP is still quite low by international standards and may converge to international levels in the future. Together with sustained economic growth, the size of the Chinese home market will become as important as the export market making Chinese firms less dependent on exports and let them focus more closely on the home market. Our results suggest that these dynamics from the demand side may have important implications for technical progress and may help to sustain high Chinese growth also in the years to come.

Part III

Appendices

A Appendix: Chapter 1

A.1 Theoretical Appendix

Proof of Lemma 1.1

Proof. Since the market of intermediates is competitive, the representative firm solves

$$\min_{\chi(\omega_i,t),L_i(t)} \int_0^{M_i(t)} p(\omega_i,t)\chi(\omega_i,t)d\omega_i + L_i(t)w(t), \tag{A.1}$$

subject to (1.3) and a given output level $y_i(t)$. Calling the multiplier of constraint (1.3) $p_i(t)$ the first order conditions are,

$$p(\omega_i,t) = \chi(\omega_i,t)^{-\frac{1}{\nu}} L_i(t)^{\frac{1}{\nu}} p_i(t),\ \forall \omega_i, \tag{A.2}$$

$$w(t) = \frac{1}{\nu-1}\left[\int_0^{M_i(t)} \chi(\omega_i,t)^{\frac{\nu-1}{\nu}} d\omega_i\right] L_i(t)^{\frac{-\nu+1}{\nu}} p_i(t). \tag{A.3}$$

Due to the iso-elastic demand (A.2) it is optimal for the monopolist to set the price equal to $\frac{\nu}{\nu-1}$ times her marginal cost, $\psi_i(t)$, resulting in (1.4). Substituting this optimal price into (A.2) gives (1.5). Using this in (A.3) yields (1.6). Profit flows are given by quantity times the mark-up, i.e. $\pi(\omega_i,t) = \chi(\omega_i,t)\left[p(\omega_i,t) - \psi_i(t)\right]$. With (1.4)-(1.6) this reduces to (1.7). Using (1.5) in (1.3) yields (1.8). Finally, the total amount of machines used in industry i is given by $\int_0^{M_i(t)} \chi(\omega_i,t)d\omega_i = M_i(t)L_i(t)$. Since each of these machines causes variable cost of $\frac{\nu-1}{\nu}$ units of intermediate input $y_i(t)$, the total number of intermediate inputs used to produce machines is given by (1.9). □

Proof of Lemma 1.2

Proof. (1.11) highlights the fact that at each point in time, the value of a firm must be equal to the R&D cost of creating a new one, $\frac{p_i(t)}{\eta}$, where we substitute $p_i(t)$ by (1.6). (1.12) is just the Hamilton-Jacobi-Bellman (HJB) representation of the zero ex-ante profit condition, i.e. $r(t)v_i(t) - \dot{v}_i(t) = \pi_i(t)$, where we make use of (1.11). □

Proof of Lemma 1.4

Proof. The current Hamiltonian reads

$$\mathcal{H} = V\left(E(t), P_N(t)\right) + \lambda(t)\left[r(t)A(t) + w(t)L - E(t)\right].$$

We can write the first-order conditions as

$$E(t)^{\epsilon-1} - \lambda(t) = 0, \tag{A.4}$$

$$r(t)\lambda(t) = \rho\lambda(t) - \dot{\lambda}(t). \tag{A.5}$$

Taking the first derivative of (A.4) with respect to time and simplifying gives (1.19). □

Proof of Proposition 1.1

Proof. The choice of numÈraire $P_D(t) = 1$ implies (see (1.1) and (1.6))

$$1 = (\nu - 1)w(t)\exp\left[-\int_0^1 \log\left[M_i(t)\right] di\right]. \tag{A.6}$$

By differentiating this with respect to time we get

$$\int_0^1 \frac{\dot{M}_i(t)}{M_i(t)} di = \frac{\dot{w}(t)}{w(t)}. \tag{A.7}$$

If we take the sum over all $i \in [0,1]$ of both sides of (1.12) and use the labor market clearing condition, (1.22), we get

$$r(t) - \frac{\dot{w}(t)}{w(t)} + \int_0^1 \frac{\dot{M}_i(t)}{M_i(t)} di = \frac{\eta L}{\nu}. \tag{A.8}$$

Combining (A.7) and (A.8) yields

$$r(t) = r = \frac{\eta L}{\nu}.$$

This implies that in *any* equilibrium, the interest rate (in terms of durable goods) must be constant over time. With a constant interest rate the Euler equation, (1.19), implies a constant expenditure growth rate $\frac{\dot{E}(t)}{E(t)} = g$, where $g > 0$ because $\frac{\eta L}{\nu} > \rho$. The asset market clearing condition, (1.23), together with (1.11) implies $\frac{\dot{A}(t)}{A(t)} = \frac{\dot{w}(t)}{w(t)}$. Finally, substituting this into the flow budget constraint, (1.18), implies $\frac{\dot{A}(t)}{A(t)} = g$. This proves (1.24) and (1.25). For (1.26) note that (A.6) and the assumption $M_i(0) = 1$, $\forall i$ implies $w(0) = \frac{1}{\nu-1}$. Next, $c_i(t)$ and $y_i(t)$ are given by (1.9) and (1.8) and if we combine (1.10) and (1.12) we get $z_i(t) = M_i(t)\left[\frac{L_i(t)-L}{\nu} + \frac{g}{\eta}\right]$. Plugging this into the market clearing condition, (1.21), implies

$$\tilde{x}_i(t) = M_i(t)\left[\frac{L_i(t)}{\nu - 1} + \frac{1}{\nu}L - \frac{g}{\eta}\right]. \tag{A.9}$$

Finally we obtain total consumption expenditures $E(t) = \int_0^1 p_i(t)\tilde{x}_i(t)di$, where $p_i(t)$ is given by (1.6). $\mathcal{E}_0$ is strictly positive since $\rho > \frac{\epsilon\eta L}{\nu}$. This assumption also ensures that the transversality condition is fulfilled and that utility is finite. □

Proof of Lemma 1.5

Proof. First, note that we can write $E(t) = \mathcal{E}_0 \exp[gt]$ (see (1.25) and (1.27)). If we use this expression and (1.2) in (1.17), we obtain (1.28).
Second, let us prove equation (1.29): since the final consumption goods are produced competitively with Cobb-Douglas technologies (implying output elasticities of the durable and non-durable sector which are equal to unity and $\alpha(i)$), we must have $p_i(t)\tilde{x}_i(t) = E(t)S_N(t)\alpha(i) + E(t)[1 - S_N(t)]$. If we substitute $p_i(t)$, $\tilde{x}_i(t)$ in this equation by the expressions (1.6) and (A.9) and use the definition of g and $\mathcal{E}_0$, we get

$$(\nu - 1)w(t)\left[\frac{L_i(t) - L}{\nu - 1} + \mathcal{E}_0\right] = E(t)S_N(t)\alpha(i) + E(t)[1 - S_N(t)].$$

If we additionally substitute $w(t)$ by (1.26) and $E(t)$ by $\mathcal{E}_0 \exp[gt]$ and simplify terms, we have

$$L_i(t) - L = S_N(t)(\nu - 1)[\alpha(i) - 1]\mathcal{E}_0. \tag{A.10}$$

Now, if we use (1.24) and (1.25) in (1.12), we get

$$\frac{\dot{M}_i(t)}{M_i(t)} = \frac{\eta[L_i(t) - L]}{\nu} + g. \tag{A.11}$$

Then, combining this with (1.6), (1.26) (and the fact that $M_i(0) = 1$, $\forall i$) we can write

$$p_i(t) = \exp\left[-\frac{\eta}{\nu}\int_0^t (L_i(\tau) - L)\,d\tau\right].$$

If we substitute $L_i(\tau) - L$ in this expression by the analog of equation (A.10) we obtain equation (1.29). □

Proof of Proposition 1.2

Proof. Substituting $p_i(t)$ in (1.28) by (1.29) and using the fact that $\int_0^1 [\alpha(i) - 1]^2 \, di = \sigma^2$,

$$S_N(t) = S_N(0) \exp\left[-\gamma\Delta t - \epsilon g t - \gamma\eta\frac{\nu - 1}{\nu}\sigma^2\mathcal{E}_0\int_0^t S_N(\tau)d\tau\right]. \tag{A.12}$$

Differentiating both sides of this equations with respect to time we obtain the following differential equation

$$\frac{\dot{S}_N(t)}{S_N(t)} = -\gamma\Delta - \epsilon g - \gamma\eta\frac{\nu - 1}{\nu}\sigma^2\mathcal{E}_0 S_N(t). \tag{A.13}$$

By solving this differential equation we obtain (1.32). Once we have solved for this, (1.33)-(1.35) follow immediately from (1.17), (A.10) as well as (1.29) and (A.12). $\square$

Proof of Proposition 1.3

Proof. (1.38) ensures that (1.14) is fulfilled at date $t = 0$ (see (1.31)). Moreover, (1.36) and (1.37) ensure that $\frac{\dot{S}_N(t)}{S_N(t)} < 0, \forall t \geq 0$ (see (A.13)). Hence, $S_N(0)$ is smaller or equal to one and it is falling over time. Consequently, (1.14) is fulfilled for all $t \geq 0$. $\square$

A.2 Empirical Appendix

First Stage Regressions

Table A.1 displays the corresponding first stage regressions to Tables 1.3 and 1.4 in Section 1.4. Clearly, our instrumental variable, denoted by the potential market share, serves as a strong instrument since the first stage regression coefficients are significant at the one percent level and the corresponding F-statistics are well above 10.

Dependent Variable: Price Growth & TFP Growth

	(1) Log market share	(2) L.Log market share	(3) L2.Log market share
Log pot. market share	1.234***		
	(0.233)		
L.Log pot. market share		1.246***	
		(0.213)	
L2.Log pot. market share			1.274***
			(0.221)
N	180	150	120
R^2	0.472	0.527	0.526
F-statistic	28.13	34.23	33.33

Table A.1: First stage regressions corresponding to Tables 1.3 and 1.4

Notes: Standard errors are clustered at the industry level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include year fixed effects (4-6 intervals) and industry fixed effects (30 groups). The total sample period runs from 1977-2007, but observations are averaged over five year time intervals. The instrumental variable - denoted by Log potential market share - is constructed as described in Section 1.4, i.e. it is $\log \tilde{s}_i(t-l)$. "L." and "L2." denotes a one and two period lag respectively (i.e. $l = 5$ and $l = 10$). The reported R^2 measures the marginal contribution of our instrument when all control variables are already included in the model (it equals the partial R^2).

Robustness Checks

In the following we perform two additional robustness tests of our estimates. First, Table A.2 and A.3 show the results if we additionally control for an industry's labor income share in value-added. Conditional on industry fixed effects, we find the labor income share being (most of the time) statistically significant. This in turn suggests that (the scope for) mechanization is an important channel of technical progress. However, the results of the market size effect are still there (although the coefficients are less precisely estimated, especially in the case of the TFP growth rate). Moreover, note that especially the OLS estimates drop in size and precision, suggesting that our IV estimate is less prone to omitted variable bias and OLS underestimates the true market size effect.

Dependent variable: Price Growth

	(1)	(2)	(3)	(4)
L.Log market share	-0.393**		-0.506***	
	(0.162)		(0.169)	
L2.Log market share		-0.205		-0.301**
		(0.127)		(0.153)
Log labor share	-1.144**	-1.310**	-1.089**	-1.239**
	(0.517)	(0.626)	(0.494)	(0.591)
N	150	120	150	120
R^2	0.567	0.604	0.561	0.601
Method	OLS	OLS	IV	IV

Table A.2: Price growth – omitted variables

Notes: Standard errors are clustered at the industry level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include year fixed effects (4-5 intervals) and industry fixed effects (30 groups). The total sample period runs from 1977-2007, but observations are grouped into five-year intervals. The independent variables are averaged over five years, the dependent variable is calculated as the five-year log-difference. In columns 3 and 4 the Log market share is instrumented by the structural change at the final consumption good level as described in Section 1.4. The corresponding first stage regressions are found in Table A.4. "L." and "L2." denotes a one and two period lag respectively (i.e. $l = 5$ and $l = 10$ in equation (1.43)).

In a second robustness check we take a closer look at the service sector. Establishing the existence of a market size effect in this sector is particularly interesting for two reasons: (i) starting with Baumol's influential study (1967) there exist enormous doubts about the innovation potential of this sector, and (ii) being the main benefiter of modern structural change this sector has expanded tremendously (in nominal terms). Hence, showing positive evidence for the market size effect within the service industries will be of growing importance for the future.

Table A.5 and A.6 show the main results if we split the economy in the "service sector" and the "rest" and run the regressions separately.[1] Given the restricted sample size of our

[1] For a classification of industries into services, non-services respectively the reader is referred to regression output Tables A.5 and A.6.

Dependent variable: TFP Growth

	(1)	(2)	(3)	(4)
L.Log market share	0.154*		0.231**	
	(0.082)		(0.109)	
L2.Log market share		0.032		0.141
		(0.103)		(0.108)
Log labor share	0.774*	0.697	0.736*	0.616
	(0.405)	(0.437)	(0.393)	(0.417)
N	150	120	150	120
R^2	0.634	0.644	0.630	0.638
Method	OLS	OLS	IV	IV

Table A.3: TFP growth – omitted variable

Notes: Standard errors are clustered at the industry level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include year fixed effects (4-5 intervals) and industry fixed effects (30 groups). The total sample period runs from 1977-2007, but observations are grouped into five-year intervals. The independent variables are averaged over five years, the dependent variable is calculated as the five-year log-difference. In columns (3) and (4) the Log market share is instrumented by the structural change at the final consumption good level as described in Section 1.4. The corresponding first stage regressions are found in Table A.4. "L." and "L2." denotes a one and two period lag respectively (i.e. $l = 5$ and $l = 10$ in equation (1.43)).

Dependent Variable: Price Growth & TFP Growth

	(1)	(2)
VARIABLES	L.Log market share	L2.Log market share
L.Log potential market share	1.213***	
	(0.222)	
L2.Log potential market share		1.205***
		(0.207)
Log labor share	0.293	0.493
	(0.235)	(0.312)
N	150	120
R^2	0.519	0.520
F-statistic	29.91	33.75

Table A.4: First stage regressions corresponding to Tables A.2 and A.3

Notes: Standard errors are clustered at the industry level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include year fixed effects (4-6 intervals) and industry fixed effects (30 groups). The total sample period runs from 1977-2007, but observations are averaged over five year time intervals. The instrumental variable - denoted by Log potential market share - is constructed as described in Section 1.4, i.e. it is $\log \tilde{s}_i(t-l)$. "L." and "L2." denotes a one and two period lag respectively (i.e. $l = 5$ and $l = 10$). The reported R^2 measures the marginal contribution of our instrument when all control variables are already included in the model (it equals the partial R^2).

subsamples and the demanding regression specification (including a full set of industry - and time fixed effects), we find positive evidence for the existence of a market size effect. As before, our IV estimate is significantly larger than the OLS estimate hinting to a downward bias in OLS. Among services, we find that a one percent increase in market size translates into an increase in the industry-specific TFP growth rate of 0.38 percentage points over five years (see column (4) in Table A.5). In the non-service industries this coefficient is slightly smaller and insignificant. Thus, the application of our IV stratetgy hints to an ex-ante surprising result of a stronger market size effect on TFP growth within services.

Service Sectors

	(1)	(2)	(3)	(4)
Dependent Variable	price growth	price growth	TFP growth	TFP growth
L.Log market share	-0.222***	-0.485***	0.132	0.385***
	(0.061)	(0.123)	(0.100)	(0.139)
N	70	70	70	70
R^2	0.717	0.650	0.630	0.573
Method	OLS	IV	OLS	IV

Table A.5: Robustness check – sample split

Notes: Standard errors are clustered at the industry level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include year fixed effects (5 intervals) and industry fixed effects (14 groups). The total sample period runs from 1977-2007, but observations are grouped into five-year intervals. The independent variables are averaged over five years, the dependent variable is calculated as the five-year log-difference. In columns (2) and (4) the Log market share is instrumented by the structural change at the final consumption good level as described in Section 1.4. The corresponding first stage regressions are found in Table A.7. "L." and "L2." denotes a one and two period lag respectively (i.e. $l = 5$ and $l = 10$ in equation (1.43)). Sectors E, G-O are classified as service sectors (NACE revision 1 classification).

Agriculture, Mining, Manufacturing and Construction

	(1)	(2)	(3)	(4)
Dependent variable	price growth	price growth	TFP growth	TFP growth
L.Log market share	-0.749**	-0.857**	0.266	0.299
	(0.316)	(0.420)	(0.205)	(0.286)
N	80	80	80	80
R^2	0.437	0.435	0.543	0.543
Method	OLS	IV	OLS	IV

Table A.6: Robustness check – sample split

Notes: Standard errors are clustered at the industry level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include year fixed effects (5 intervals) and industry fixed effects (16 groups). The total sample period runs from 1977-2007, but observations are grouped into five-year intervals. The independent variables are averaged over five years, the dependent variable is calculated as the five-year log-difference. In columns (2) and (4) the Log market share is instrumented by the structural change at the final consumption good level as described in Section 1.4. The corresponding first stage regressions are found in Table A.7. "L." and "L2." denotes a one and two period lag respectively (i.e. $l = 5$ and $l = 10$ in equation (1.43)). Sectors A-D, F are classified as non-service sectors (NACE revision 1 classification).

Dependent Variable: Price Growth & TFP Growth

VARIABLES	(1) L.Log market share	(2) L.Log market share
L.Log potential market share	0.730***	1.181***
	(0.167)	(0.294)
N	70	80
R^2	0.303	0.466
F-statistic	19.17	16.10
Sectors	Services	Non-Services

Table A.7: First stage regressions corresponding to Tables A.5 and A.6

Notes: Standard errors are clustered at the industry level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include year fixed effects (6 intervals) and industry fixed effects (14-16 groups). The total sample period runs from 1977-2007, but observations are averaged over five year time intervals. The instrumental variable - denoted by Log potential market share - is constructed as described in Section 1.4, i.e. it is $\log \tilde{s}_i(t-l)$. "L." and "L2." denotes a one and two period lag respectively (i.e. $l = 5$ and $l = 10$). The reported R^2 measures the marginal contribution of our instrument when all control variables are already included in the model (it equals the partial R^2).

The Channel of R&D Investments

An additional step in our empirical exercise is to analyze the channel through which a change in market size affects the evolution of relative productivity and consequently relative prices. Our theory suggests that R&D investments play the crucial role of determining productivity growth and hence relative prices. Therefore, we turn to evaluating the effect of an increase in market share on industry-specific R&D expenditures. Since our dataset on R&D stocks is limited in size and the flow of R&D expenditures is not as volatile as TFP measures, we use annual observations for our next regression specification.[2] As in the main section above, our estimation specification looks as follows

$$d_i(t) = \delta \log s_i(t) + \kappa_i + \phi(t) + u_i(t), \tag{A.14}$$

where $d_i(t)$ now represents the growth rate of the industry-specific R&D stock. It is calculated as the log-differences between two consecutive years t and $(t-1)$. $s_i(t)$ is the market size of industry i, κ_i and $\phi(t)$ represent a full set of industry and time fixed effects and $u_i(t)$ is an error term.

Table A.8 displays the results using the true market share as our independent variable. As expected there seems to be an immediate effect of market size on the industry-specific R&D activity. For example, a 1 percent increase in the industry's contemporaneous market share increases the amount of investments into research by 0.072 percentage points, while the past market share does not show any effect. Note that the lagged market share is computed as the market share in period $(t-5)$. Due to the potential endogeneity of our measure of market size, we again re-run the regression specification. Using our instrument, column 1 of Table A.9 shows that the effect increases to 0.15 percentage points. Again, we find the effect of R&D investments to be an immediate reaction to an increased market size. Controlling for the industry-specific labor share increases the coefficient further to 0.164, (which remains significant at the significance level of ten percent). Although, our coefficients are not as robust as for TFP and Prices, we are convinced that R&D investments are one of the main vehicles through which market size acts on an industry's TFP growth rate.[3]

[2]The autocorrelation between the R&D expenditure flow and its one-year lag is 0.90.

[3]Table A.10 shows the first stage regression results.

Dependent variable: R&D Investment Growth

	(1)	(2)	(3)	(4)
Log market share	0.072**		0.100***	0.080*
	(0.032)		(0.037)	(0.046)
L.Log market share		-0.054	-0.078	
		(0.048)	(0.048)	
Log labor share				0.032
				(0.065)
N	345	315	315	345
R^2	0.374	0.368	0.404	0.376
Method	OLS	OLS	OLS	OLS

Table A.8: OLS regression of R&D investment growth

Notes: Standard errors are clustered at the industry level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include year fixed effects (21-23 years) and industry fixed effects (15 groups). The total sample period runs from 1980-2003. The dependent variable is calculated as the two-year log difference in the industry's R&D stock. In concordance with the baseline regressions, "L." denotes a one period lag (i.e. $l = 5$).

Dependent variable: R&D Investment Growth

	(1)	(2)	(3)
Log market share	0.150*		0.164*
	(0.0811)		(0.0867)
L.Log market share		0.00418	
		(0.0567)	
Log labor share			0.106
			(0.0695)
N	345	315	345
R^2	0.340	0.349	0.345
Method	IV	IV	IV

Table A.9: IV regression of R&D investment growth

Notes: Standard errors are clustered at the industry level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include year fixed effects (21-23 years) and industry fixed effects (15 groups). The total sample period runs from 1980-2003. The dependent variable is calculated as the two-year log difference in the industry's R&D stock. The Log market share is instrumented by the structural change at the final consumption good level as described in Section 1.4. The corresponding first stage regressions are found in Table A.10. In concordance with the baseline regressions, "L." denotes a one period lag (i.e. $l = 5$).

Dependent variable: R&D Investment Growth

	(1)	(2)	(3)
VARIABLES	Log market share	L.Log market share	Log market share
Log pot. market share	0.842***		0.756***
	(0.187)		(0.214)
L.Log pot. market share		0.852***	
		(0.138)	
Log labor share			-0.761***
			(0.115)
N	345	315	345
R^2	0.298	0.265	0.310
F-statistic	20.33	38.01	12.48
Note			Incl. controls

Table A.10: First stage regressions corresponding to Table A.9

Notes: Standard errors are clustered at the industry level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include year fixed effects (21-23 years) and industry fixed effects (15 groups). The total sample period runs from 1980-2003. The instrumental variable - denoted by Log potential market share - is constructed as described in Section 1.4, i.e. it is $\log \tilde{s}_i(t-l)$. "L." denotes a one period lag (i.e. $l = 5$). The reported R^2 measures the marginal contribution of our instrument when all control variables are already included in the model (it equals the partial R^2).

The Effect on Patents

In a last exercise, we test the market size effect using the log number of patents as dependent variable. Similar to Acemoglu and Linn (2004), we use patents as an alternative measure for R&D activity of industries. The advantage to TFP data is that patents do not capture any other effects apart from innovation behavior. The disadvantage is that only specific inventions are captured by patent counts and thus we only cover 11 industries with this data (mainly the manufacturing sector).
Let us denote the industry-specific number of patents by $N_i(t)$, then our estimated regression looks as follows

$$\log N_i(t) = \delta \log s_i(t-l) + \kappa_i + \phi(t) + u_i(t), \tag{A.15}$$

where $N_i(t) = \sum_{k=0}^{4} N_i(t-k)$ measures the absolute number of patents attributed to industry i within a five-year spell. $s_i(t)$ measures again the market size of industry i in value-added terms

$$s_i(t-l) = \frac{1}{5}\sum_{k=0}^{4} \frac{va_i(t-l-k)}{GDP(t-l-k)}.$$

κ_i and $\phi(t)$ represent a full set of industry and time fixed effects and $u_i(t)$ is an error term. Table A.11 displays the results using the true market share as our independent variable. As for the baseline specification of TFP growth, the main effect of an increased market share on patents seems to come with a lag of five to ten years. For instance, column (2) suggests that an increase in market size by one percent increases the number of patents by 0.88 percent after 5 years. And although the contemporaneous market size also shows a positive significant effect (see column (1)), column (4) of Table A.11 reveals that this is driven largely by the autocorrelation of the lagged and the contemporaneous market share. Due to endogeneity of our actual market size measure, Table A.12 repeats the approach using our instrumental variable. For instance, increasing the market share by one percent increases the number of industry-specific patents by more than 2 percent over the interval of five years (see column (2)).[4] Although these findings are accurately estimated, some care must be taken due to the small dataset we rely on. Nevertheless we have confidence in these results as they tell the same story as our main specification and more important are in line with our theory. The larger the relative market size, the larger the industry-specific R&D investments and thus the productivity growth rate (measured in TFP or patents).

[4] First stage results are displayed in Table A.13.

Dependent variable: Log Number of Patents

	(1)	(2)	(3)	(4)
Log market share	0.878*			0.536
	(0.478)			(0.463)
L.Log market share		0.877**		0.615***
		(0.370)		(0.200)
L2.Log market share			0.744**	
			(0.375)	
N	44	33	22	33
R^2	0.993	0.996	0.998	0.996
Method	OLS	OLS	OLS	OLS

Table A.11: OLS regression of patents

Notes: Standard errors are clustered at the industry level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include year fixed effects (2-4 intervals) and industry fixed effects (11 groups). The total sample period runs from 1979-1999, but observations are grouped into five year time intervals. The independent variables are averaged over five years, the dependent variable is calculated as the log number of patents received within five years. "L." and "L2." denotes a one and two period lag respectively (i.e. $l = 5$ and $l = 10$).

Dependent variable: Log Number of Patents

	(1)	(2)	(3)
Log market share	1.582***		
	(0.590)		
L.Log market share		2.057***	
		(0.728)	
L2.Log market share			1.913**
			(0.872)
N	44	33	22
R^2	0.991	0.991	0.996
Method	IV	IV	IV

Table A.12: IV regression of patents

Notes: Standard errors are clustered at the industry level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include year fixed effects (2-4 intervals) and industry fixed effects (11 groups). The total sample period runs from 1979-1999, but observations are grouped into five year time intervals. The independent variables are averaged over five years, the dependent variable is calculated as the log number of patents received within five years. The Log market share is instrumented by the structural change at the final consumption good level as described in Section 1.4. The corresponding first stage regressions are found in Table A.13. "L." and "L2." denotes a one and two period lag respectively (i.e. $l = 5$ and $l = 10$).

Dependent variable: Log Number of Patents

VARIABLES	(1) Log market share	(2) L.Log market share	(3) L2.Log market share
Log pot. market share	0.872***		
	(0.161)		
L.Log pot. market share		0.655***	
		(0.196)	
L2.Log pot. market share			0.531**
			(0.217)
N	44	33	22
R^2	0.460	0.369	0.323
F statistik	29.33	11.20	5.97

Table A.13: First stage regressions corresponding to Table A.12

Notes: Standard errors are clustered at the industry level and displayed in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include year fixed effects (4 intervals) and industry fixed effects (11 groups). The total sample period runs from 1979-1999, but observations are grouped into five year time intervals. The instrumental variable - denoted by Log potential market share - is constructed as described in Section 1.4, i.e. it is $\log \tilde{s}_i(t-l)$. "L." and "L2." denotes a one and two period lag respectively (i.e. $l = 5$ and $l = 10$). The reported R^2 measures the marginal contribution of our instrument when all control variables are already included in the model (it equals the partial R^2).

A.3 Data Appendix

Data Sources and Descriptive Statistics

First, we use the US National Income and Product Accounts (NIPA), which are prepared by the Bureau of Economic Analysis (BEA), US Department of Commerce. Specifically, NIPA tables 2.4.5 and 2.4.4 contain information about personal consumption expenditures and the corresponding consumer good price index. Data on the production side of the economy is extracted from NIPA tables 1.2.4 and 1.2.5, which tell us how different sectors contribute to aggregate GDP and contain information about the corresponding producer price index. Finally, information on population measures is obtained from NIPA table 7.1.[5] Table A.14 shows the descriptive statistics of the NIPA data.

Second, to construct our instrument we use the 2002 US Benchmark Input-Output

Descriptive Statistics

Variable	Obs.	Mean	Std.Dev.	Min	Max
Total personal expenditures	84	2525.601	3263.124	45.9	11119.5
Non-durable expenditures	84	624.036	719.484	20	2563
Durable expenditures	84	316.775	388.72	3.8	1218.8
Rel. non-durable consumer's price	84	0.592	0.232	0.399	1.366
Non-durable production	67	693.516	611.106	73	2175.7
Durable production	67	742.782	715.322	37.9	2278.7
Rel. non-durable producer's price	67	0.680	0.198	0.498	1.209
Population (midyear)	84	207307	59564.71	121878	314278

Table A.14: Descriptive Statistics-NIPA Tables

Notes: The table shows descriptives for personal consumption expenditures, prices and population in the US between 1929-2012. Due to availability, production data is given between 1946-2012. All data is given in nominal values and consumption and production data is denoted in billions of US$.
Sources: BEA, NIPA tables 1.2.4, 1.2.5, 2.4.4, 2.4.5, 7.1.

Accounts from the BEA. In particular, we use the standard Make and Use tables after redefinition, the Import matrix and the "Personal Consumption Expenditure (PCE) Bridge Table". All I-O tables are at the most detailed level which follows the 6-digit NAICS classification and contain 430 industries.

Third, our main data source for the empirical section is the 2009 release of the EU KLEMS database, which provides us with information about industry-specific value-added, intermediate inputs, prices and TFP.[6] For the US it spans from 1977-2007 and differentiates

[5]Further details are found in the NIPA handbook (2011): "Concepts and Methods of the US National Income and Product Accounts", ch.1-9, available at www.bea.gov.

[6]The source data comes from National Accounts and is obtained from National Statistical Institutes, Eurostat and country specific EU KLEMS consortium partners. For the US this is the Groningen Growth and Development Centre at the University of Groningen, The Netherlands. O'Mahony and Timmer (2009) provide an overview of the construction of the EU KLEMS database.

the aggregate economy into 32 industries, whereof we exclude "private households with employed persons" and "extra-territorial organizations and bodies" in our analysis. Table A.15 displays the corresponding descriptive statistics.

Descriptive Statistics

Variable	Obs.	Mean	Std.Dev.	Min	Max
TFP growth	180	0.043	0.181	-0.519	0.789
VAD price growth	180	-0.023	0.207	-0.785	1.255
Log value-added share	180	-3.758	0.900	-5.774	-2.115
Log expenditure share	180	-3.941	1.104	-6.453	-2.164
Log intermediate share	180	-0.720	0.296	-1.521	-0.125
Log labor share	180	-0.493	0.509	-2.82	-0.077

Table A.15: Descriptive Statistics - EU KLEMS database

Notes: The table shows descriptives for variables used in the empirical section. Log expenditure share denotes the instrumental variable as described in Section 1.4. Log labor share is total labor income as its share in total gross output, share in total value-added respectively. All data is given in nominal terms and grouped into five year intervals.
Source: EU KLEMS 2009 release for the US

Finally, for the robustness checks of our empirical results, we obtain data on industries' R&D expenditures and patents from databases that are linked to the EU KLEMS.[7] R&D information was originally taken from the "OECD Research and Development in Industry Database" (ANBERD), while patent statistics were derived from the NBER Patent Citations Data File (see Hall et. al, 2001). For the US, the R&D dataset covers 15 industries (excluding "Market Services") and spans from 1980-2003. The patent database covers 11 industries and spans from 1974-1999, whereof we use the data from 1979-1999. Note that patents were assigned to years according to the date of application and to the "country of first inventor". Further, one patent may be assigned to multiple industries. Table A.16 and Table A.17 give descriptive figures for the relevant variables of the R&D dataset and the patent datafile respectively.

Descriptive Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
R&D stock growth	345	0.029	0.050	-0.087	0.366
Log value-added share	345	-4.356	0.753	-5.930	-3.028
Log expenditure share	345	-4.649	0.813	-6.459	-3.314
Log labor share	345	-0.451	0.322	-1.495	-0.0001

Table A.16: Descriptive Statistics - R&D Expenditure

Notes: The table shows the descriptives of variables used in the regressions of R&D investment growth. R&D stock growth is calculated as the two-year log difference and labor share denotes total labor income as its share in total value-added. Log expenditure share denotes the instrumental variable as described in Section 1.4. All data is given in nominal terms.
Source: EU KLEMS Linked Data - 2008 Release.

[7]Detailed information can be found in O'Mahony *et al.* (2008), "EU KLEMS - Linked Data: Sources and Methods", available at *www.euklems.net*.

Descriptive Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
Log patents	44	9.546	1.383	7.260	12.291
Log value-added share	44	-4.400	0.648	-5.722	-3.521
Log expenditure share	44	-4.603	0.693	-6.036	-3.339

Table A.17: Descriptive Statistics - Patent Accounts

Notes: The table shows the descriptives of variables used in the regressions of the number of patents. All data is grouped into five year intervals and Log patents is the absolute number of patents received within five years. Log expenditure share denotes the instrumental variable as described in Section 1.4. All data is given in nominal terms.
Source: EU KLEMS Linked Data - 2008 Release.

Linking Final Expenditures to Industry Value-Added

Translating final good consumption expenditures into industry value-added can be split into two main tasks. First, we use the PCE Bridge Table to match final good consumption lines into I-O commodities. In the later step, we rely on the US specific total requirement matrix that allows us to decompose the production of final goods into its intermediate components.

The Application of the Personal Consumption Expenditure Bridge Table

As outlined in Section 3, the first task in translating consumption expenditures to industry value-added is to remove distribution costs from consumption expenditures and to decompose expenditure on final goods into the shares that accrue to all intermediates. The 2002 PCE Bridge Table now helps to resolve both issues, which we will visualize with a brief example in the following. To best demonstrate the application of the Bridge Table, suppose we have two different consumption goods (think of cars and food), which are denoted by j, and assume distribution costs only consist of transportation costs. On the production side, there are three different commodities, denoted by i, where one commodity corresponds to the transportation commodity and the others are steel and grain for instance. Suppose it requires both intermediate goods, grain and steel, to produce one unit of food but car is made only of steel. Then our example PCE Bridge table looks as follows

$$PCE = \begin{bmatrix} PU_{i=grain,j=food} & PR_{i=grain,j=food} & T_{i=grain,j=food} \\ PU_{i=steel,j=food} & PR_{i=steel,j=food} & T_{i=steel,j=food} \\ PU_{i=steel,j=car} & PR_{i=steel,j=car} & T_{i=steel,j=car} \end{bmatrix},$$

where PU_{ij} indicates expenditures on consumer good j that accrues to commodity i (in purchaser's prices). $PU_j = \sum_i PU_{ij}$ are aggregate expenditures on good j that we observe in the BEA, NIPA table 2.4.5. PR_{ij} denotes the aggregate value going to commodity i through expenditures on good j (in producer's prices), and T_{ij} is the transportation cost that is specific to good j and commodity i. As transportation costs are the difference between producer's and purchaser's price, it must be that $T_{ij} = PU_{ij} - PR_{ij}$. Let C_{ij} denote the share that goes to each commodity i, if 1 US$ is spent on good j, then $C_{ij} = \frac{PR_{ij}}{PU_j}$. Finally, the consumption good specific distribution margin equals $DM_j = \frac{\sum_i T_{ij}}{PU_j}$. Using this information, we form a Final Bridge Table that later will be matched to the

Domestic Total Requirement Matrix. In our example, the Final Bridge Table is given by

$$FBT = \begin{bmatrix} C_{i=grain,j=food} & C_{i=grain,j=car} \\ C_{i=steel,j=food} & C_{i=steel,j=car} \\ DM_{food} & DM_{car} \end{bmatrix}.$$

Note from above that the final good of car is produced using only the intermediate of steel, such that $C_{i=grain,j=car} = 0$ for our specific example. The Final Bridge Table then is a commodity-by-consumption line matrix where rows are associated with commodities and columns with the different consumption goods (two in this case). Each entry in column j shows the share of input of commodity i required to produce output of consumption good j worth of one dollar.

Derivation of the Domestic Total Requirement Matrix (DTRM) in value-added

To construct the matrix that links the consumption to the production side of the economy, we will use the latest release of the 2002 Benchmark I-O Tables of the US In general, the total requirement matrix serves this task, which however does not account for imports. Sticking to our previous example, if all grain were imported from Mexico, an increase in the demand for food would have no effect on the US grain industry. Thus, we require a total requirement matrix that "is cleaned" from imports. In the following we describe how we construct the DTRM and how to convert it in value-added terms. For ease of notation, we first define several necessary objects:[8]

- g: A $(n \times 1)$ vector that shows the total output of each industry.
- q: A $(n \times 1)$ vector that shows the total output of each commodity.
- X: A $(n \times n)$ commodity-by-industry matrix denoting the imports of each commodity by industry.
- U: The middle portion of the Use Table, where each column shows for a given industry the commodities used in the production process. The table is a $(n \times n)$ commodity-by-industry matrix.
- $\bar{U}$: Denotes the $(n \times n)$ Domestic Use Table.
- V: The $(n \times n)$ industry-by-commodity Make Matrix. For a given commodity, each column shows the amount produced in each industry.

[8]The notation and method follows chapter 12 of the manual (2009), "Concepts and Methods of the US National Input-Output Accounts", available at www.bea.gov.

- B: The $(n \times n)$ commodity-by-industry Direct Requirement Matrix. Entries in each column show the proportion of each commodity used by an industry to produce output worth one dollar.

- W: A $(n \times n)$ industry-by-commodity matrix. For a given commodity, each entry within a column shows the proportion of that commodity produced in each industry.

- I: A $(n \times n)$ Identity matrix.

- e: A $(n \times 1)$ vector that shows final demand for each commodity.

- va: A $(n \times 1)$ vector that shows the value-added that is generated by final expenditure.

- v: A $(n \times 1)$ vector that shows the value-added coefficients of each industry.

- $\hat{}$: If this symbol is placed over a vector it denotes a square matrix, which contains the vector's elements on its main diagonal and zeros elsewhere.

The first step is to remove intermediate imports from the Use Table (U) in order to derive the Domestic Use Table ($\bar{U}$)

$$\bar{U} = U - X.$$

From here we calculate the Domestic Direct Requirement Matrix (B) and using the information from the Make Table (V), we form the Market Share Matrix (W)

$$B = \bar{U}\hat{g}^{-1},$$
$$W = V\hat{q}^{-1}.$$

The resulting matrices are used in I-O accounts to show the relation between input and output within each economy. Namely, each economy is described by the following two identities

$$q = Bg + e,$$
$$g = Wq.$$

The first identity says that the dollar amount of (domestically) produced output equals the sum of the amount used by industries as intermediates plus final demand. The second equation states that the output of each industry equals the sum of that industry's share of production of all domestically produced commodities. Using this information, we solve for q to obtain $q = (I - BW)^{-1} e$ and substitute it back into the second equation. This gives

$$g = W (I - BW)^{-1} e.$$

This identity states that the output of each industry equals the sum of the industry's inputs required to meet total final demand. The middle matrix, $W (I - BW)^{-1}$, then gives the Domestic Total Requirement Matrix (DTRM). Finally, denote the DTRM in terms of value-added as DV, then

$$DV = \hat{v} DTRM,$$

where $DTRM = W (I - BW)^{-1}$.

While the Final Bridge Table shows which commodities are required in order to produce a certain consumption good, the Domestic Total Requirement Matrix in value-added terms, DV, links demand for a certain commodity to value-added generated in industries. Multiplication of both tables gives an industry-by-consumption line matrix where rows are associated with industries and columns with final consumption goods. Entries in each column show the value-added generated within industry i when consumption good j is demanded. Denote the final matrix as DVB, then

$$DVB = DV \cdot FBT,$$

which gives us a (430×76) matrix. By multiplying this matrix with the vector of final consumption expenditures, we obtain the industry-specific market share (in terms of value-added) that serves as our instrument. Finally, we use the original EU KLEMS - NAICS 2002 correspondence table to match our instrument to productivity measures from the EU KLEMS database.[9]

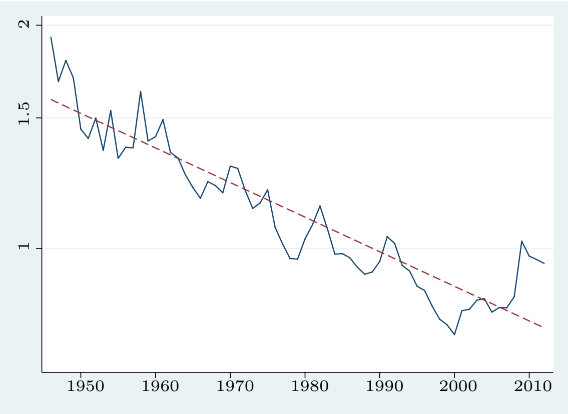
TFP Growth at the Industry Value-Added Level

To construct a weighted measure of TFP growth for durables and non-durables, we use the information obtained from the previous matrix, DVB. Entries in each column can

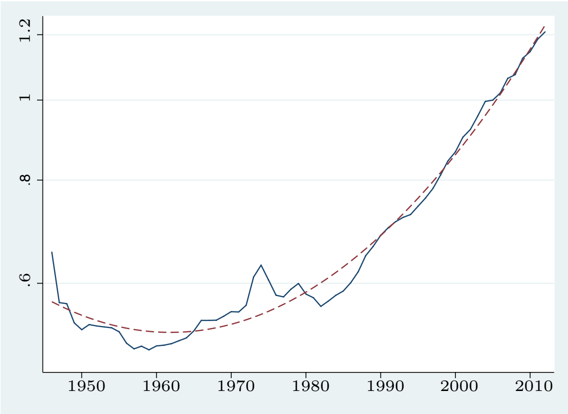
[9] The industries' market share is classified according to the US 6-digit NAICS classification, whereas the EU KLEMS uses its own classification (that closely follows the NACE 1.1 system). We obtained the original EU KLEMS - NAICS 2002 correspondence table from the US specific EU KLEMS consortium partner, the University of Groningen.

be interpreted as the industry-specific input coefficients, α_{ij}, in the production of final consumption good, j. Using the information on personal consumption expenditures from the 2002 NIPA table 2.4.5 we sum up expenditures on all 76 consumption lines into total expenditures on durables, non-durables and on services. Further, we construct expenditure weights for each of the three aggregated lines (e.g. the share of total expenditure on durables that accrues to cars, etc.). Using these information, we calculate the corresponding input coefficients, α_{ij}'s, on the level of the three consumption goods of durables, non-durables and services. These new input coefficients are then an expenditure share weighted average over the original α_{ij}'s. The TFP growth rate in terms of durables and non-durables is the weighted average of all intermediate industries' value-added TFP growth (where the weights are the newly constructed input-output coefficients).

A.4 Supplementary Appendix



(a) GDP non-durables relative to durables



(b) Relative price of non-durables

Figure A.1: **Relative GDP and relative price of the non-durable sector relative to the durable sector**

Notes: The figure plots the relative nominal GDP of non-durables to durables (which includes investments) and the corresponding producer price for the US between 1946-2012 on a logarithmic scale. In Panel (a), regressing the logarithmized relative GDP on a constant and the year gives a slope estimate of -0.01074 with a standard error of 0.00057. In Panel (b) the coefficients of regressing the logarithm of the relative price on a constant and the year in level and squared gives the slope coefficients -1.3364 (0.0616) and 0.00034 (0.00002), respectively, where standard errors are in parentheses.
Source: BEA, NIPA tables 1.2.4 and 1.2.5.

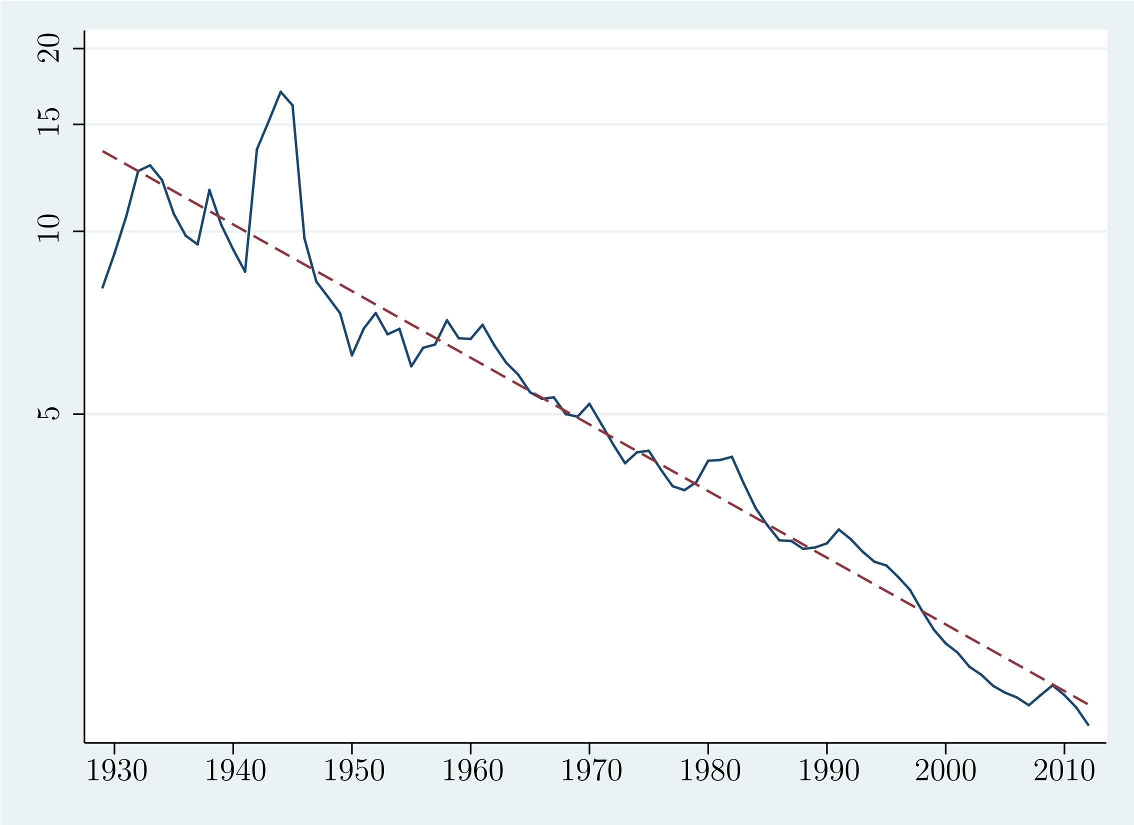


Figure A.2: **Personal consumption of non-durables quantities relative to durables quantities**

Notes: The figure plots the real personal consumption of quantities of non-durable goods relative to quantities consumed of durable goods in the US for 1929-2012 on a logarithmic scale. The price indices of durable and non-durable goods are normalized to 1 in 2005. If we regress the logarithm of the relative quantity on a constant and the year, the slope coefficient is -0.02522 with a standard error of 0.00071.
Source: BEA, NIPA tables 2.4.4 and 2.4.5.

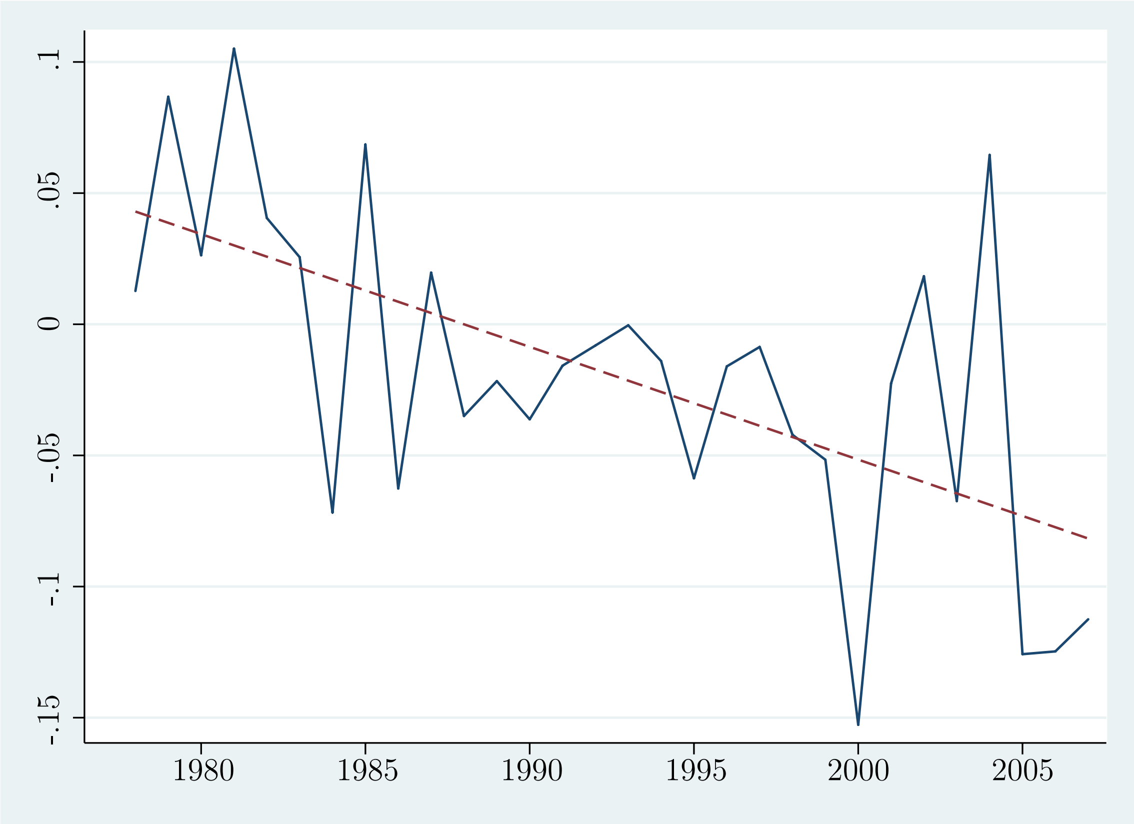


Figure A.3: **Difference between TFP growth rates of non-durables and durables**

Notes: The figure plots the difference between output share weighted TFP growth rates of non-durables and TFP growth of durables for the US between 1977-2007. The classification refers to the one on the value-added level. Wood and of Wood and Cork; Other Non-Metallic Mineral; Basic Metals and Fabricated Metal; Machinery, NEC; Electrical and Optical Equipment; Transport Equipment; and Manufacturing NEC, Recycling are classified as durables whereas Food, Beverages and Tobacco; Textiles, Textile, Leather and Footware; Pulp, Paper, Printing and Publishing; and Chemical, Rubber, Plastics and Fuel are non-durables. The slope of the fitted line is given by -0.0043 with a standard error of 0.0011.
Source: EU KLEMS, own calculations.

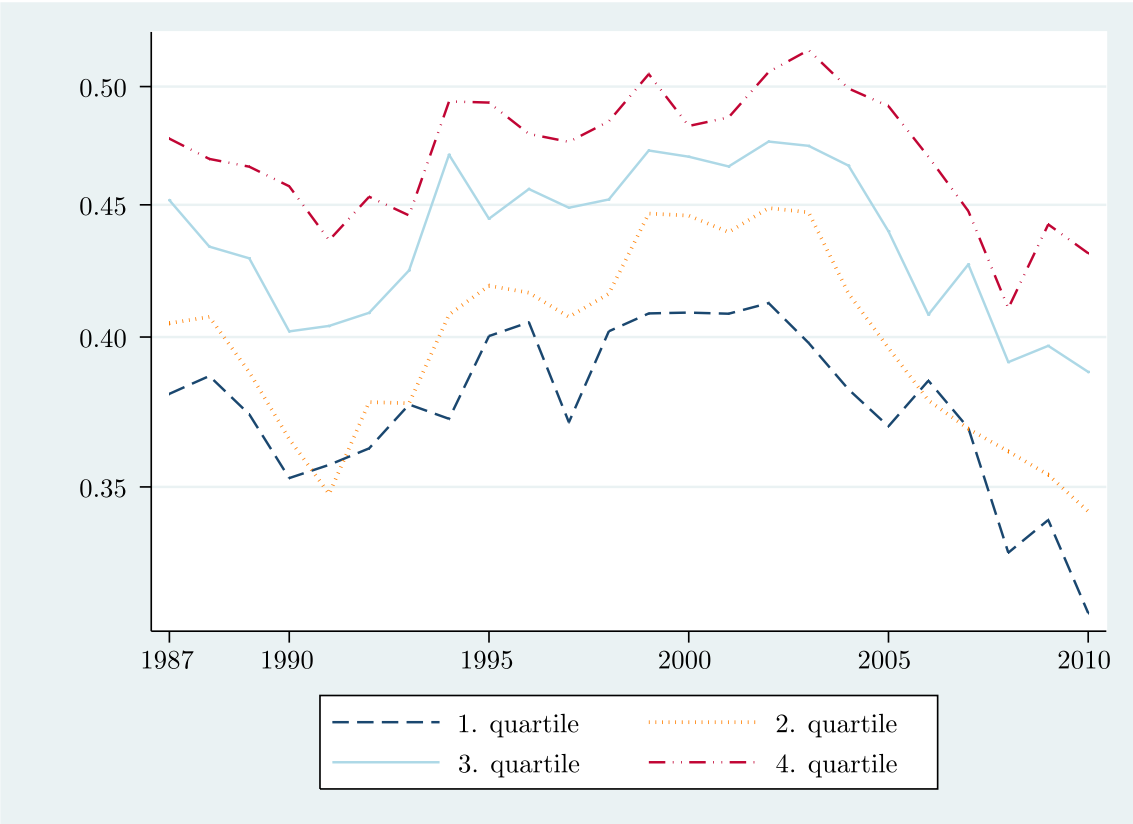


Figure A.4: **Fraction of total goods expenditures devoted to durables for rich and poor households**

Notes: The figure plots the fraction of total goods expenditures devoted to durables for each income quartile of the US for the years 1987-2010 on a logarithmized scale. The following expenditure categories are considered as durable goods: entertainment, vehicles and house furnishings & equipment expenses. Total goods expenditures are calculated as total expenditures minus service expenditures. The following categories are considered as services: food away from home; shelter; utilities, fuels, and public services; other vehicle expenses; public transportation; health care; personal care; education; cash contributions; personal insurance and pensions. The remaining categories are considered as non-durable goods. The sample consists of expenditure data of 450,602 quarters (and 165,887 households). Observations with missing income reports, with non-positive food expenditures or with an expenditure share of goods outside $[0, 1]$ have been excluded. The quartiles refer to total household after tax labor earnings plus transfers per OECD-modified equivalence scale. If we observe for a household more than one income report, the income data of the year in which the expenditure quarter lies is taken.
Source: Consumer Expenditure Survey.

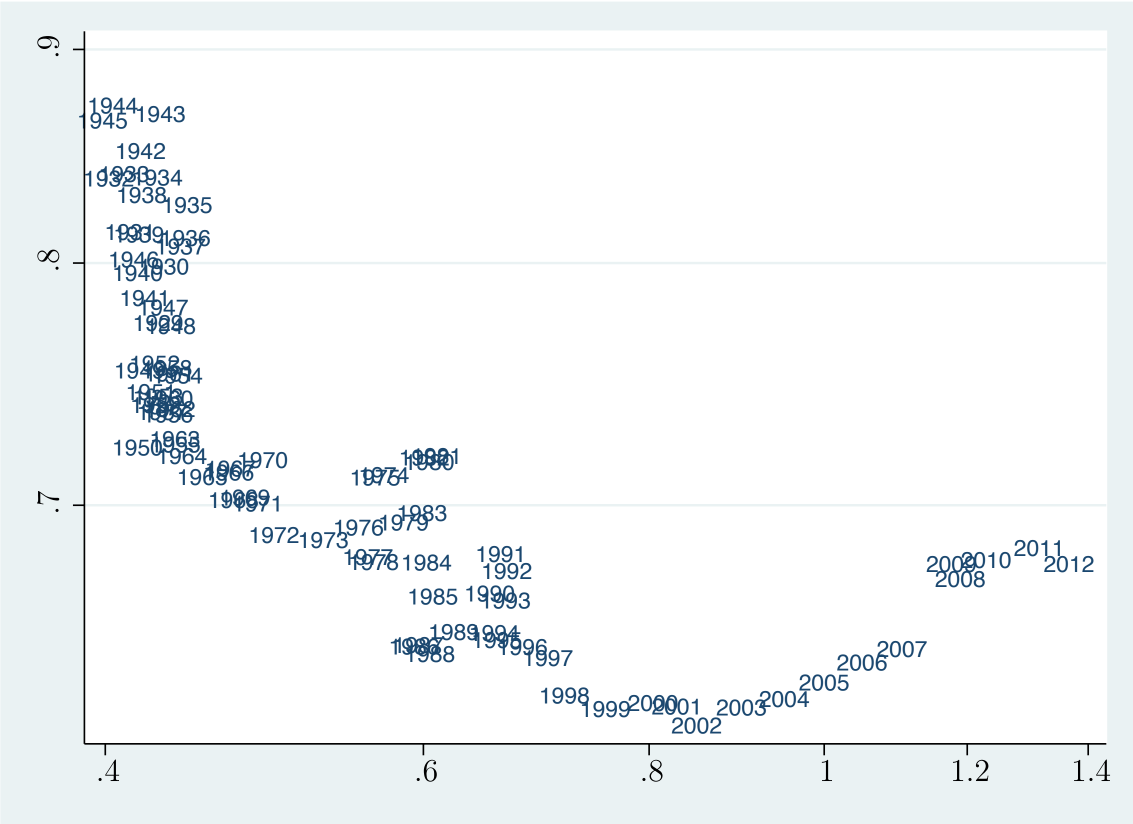


Figure A.5: **Non-durable expenditure share and its relative price**

Notes: The figure scatters the nominal expenditure share devoted to non-durables (as a fraction of total goods expenditures) against the relative price of non-durables in the US for 1929-2012 on a logarithmic scale. The durable good price index was normalized to 1 in the year 2005. Regressing the logarithm of the expenditure share on a constant and the logarithm of the relative price yields a slope coefficient of -0.20828 with a standard error of 0.20967.
Source: BEA, NIPA tables 2.4.4 and 2.4.5.

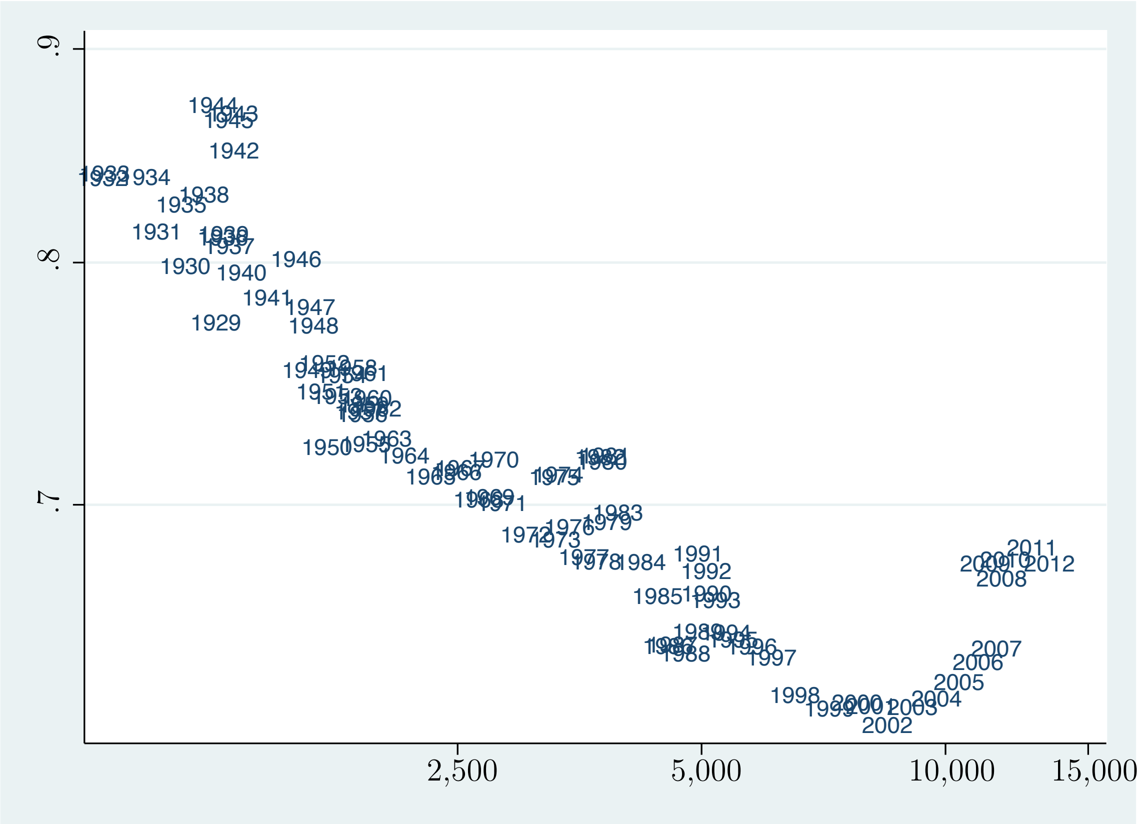


Figure A.6: **Non-durable expenditure share and per capita goods expenditures**

Notes: The figure scatters the relative nominal expenditure share devoted to non-durables (relative to aggregate goods expenditures) against aggregate goods expenditures per capita in terms of durable goods in the US for 1929-2012. The data is plotted on a logarithmic scale and the durable good price index was normalized to 1 in the year 2005. Regressing the logarithm of the expenditure share on a constant and the logarithm of the per capita expenditure in terms of durables yields a slope coefficient of -0.11040 with a standard error of 0.00624.
Source: BEA, NIPA tables 2.4.4, 2.4.5 and 7.1.

B Appendix: Chapter 2

B.1 Theoretical Appendix

This Appendix provides all formal proofs for the model.

Derivation of the Threshold Cut-off (equation (2.5))

From equation (2.5), we see that the threshold value $J^{\star}$ is such that,

$$\left(\frac{d^2\omega(J_t)}{dJ_t^2} + \frac{1-2J}{(J_t(1-J_t))^2}\right) < 0.$$

By Assumptions 2.2 and 2.4 the first term in brackets is always negative. The critical threshold value, $J^{\star}$, must satisfy, $J^{\star} < \frac{1}{2}$, since for any value $J^{\star} \geq \frac{1}{2}$ the expression is unambiguously negative. Hence, $J^{\star}$ is given as the solution to ,

$$-\frac{d^2\omega(J^{\star})}{d(J^{\star})^2}\left[(J^{\star})^4 - 2(J^{\star})^3 + (J^{\star})^2\right] + 2J^{\star} - 1 = 0.$$

Above this threshold value, technological progress leads to a larger fall in the threshold, the higher the initial threshold J_t is.

Proof of the Apprentice Productivity Schedule (condition (2.14))

Proof. The differential is,

$$\begin{aligned}
\frac{d\frac{dJ_t}{d\ln(N_t)}}{d\lambda} &= \frac{\partial\frac{dJ_t}{d\ln(N_t)}}{\partial J_t}\frac{dJ_t}{d\lambda} + \frac{\partial\frac{dJ_t}{d\ln(N_t)}}{\partial\lambda} \\
&= \frac{d^2J_t}{dJ_t d\ln(N_t)}\frac{dJ_t}{d\lambda} - \left(\frac{dJ_t}{d\ln(N_t)}\right)^2\frac{d^2\omega(J_t)}{dJ_t d\lambda} \\
&= -\left(\frac{dJ_t}{d\ln(N_t)}\right)^2\left[\left(\frac{d^2\omega(J_t)}{dJ_t^2} + \frac{1-2J}{(J_t(1-J_t))^2}\right)\left(\frac{-1}{\hat{\alpha}_\ell(J_t)}\frac{d\hat{\alpha}_\ell(J_t)}{d\lambda}\frac{dJ_t}{d\ln(N_t)}\right) + \frac{d^2\omega(J_t)}{dJ_t d\lambda}\right].
\end{aligned}$$

The final equality follows from equations (2.5) and (2.12). Simplifying this expression results in equation (2.14). □

Proof of Machine Adoption across Regions (equation (2.15))

Proof. The proof of the machine displacement across regions can be done separately for each term. From equation (2.9), the first term is,

$$\begin{aligned}\frac{\partial\left(\frac{\partial\ln(X_t)}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{\partial J_t} &= \left[\frac{dJ_t}{d\ln(N_t)}\left(\frac{1}{\overline{x}-J_t}+\frac{1}{1-J_t}\right)-\frac{d^2J_t}{d\ln(N_t)dJ_t}\right]\\ &\times\left(\frac{1}{\overline{x}-J_t}-\frac{1}{1-J_t}\right)<0.\end{aligned}$$

The first term in brackets is negative from equation (2.4) and Assumption 2.1. The second term is positive from equation (2.5). Consequently, as long as $J_t > J^\star$, technical progress in apprentice-regions leads to less machine adoption as the threshold drops at a slower rate.[1] In addition, from equation (2.12),

$$\frac{dJ_t}{d\lambda}>0,$$

making the indirect effect negative for all $J_t > J^\star$. The second term of equation (2.15), the direct effect, is

$$\frac{\partial\left(\frac{\partial\ln(X_t)}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{\partial \lambda}=-\left(\frac{1}{\overline{x}-J_t}-\frac{1}{1-J_t}\right)\left(\frac{dJ_t}{d\ln(N_t)}\right)^2\left(-\frac{\partial^2\hat{\omega}(J_t)}{\partial J_t\partial\lambda}\right).$$

The sign of this expression depends on the exact $\hat{\alpha}_\ell(i)$-slope. Collecting terms, for equation (2.15) to be negative, it must be that

$$\left[\left(\frac{1}{\overline{x}-J_t}+\frac{1}{1-J_t}\right)+\left(\frac{d^2\hat{\omega}(J_t)}{dJ_t^2}+\frac{1-2J}{(J_t(1-J_t))^2}\right)\frac{dJ_t}{d\ln(N_t)}\right]\frac{1}{\hat{\alpha}_\ell(i)}\frac{d\hat{\alpha}_\ell(J_t)}{d\lambda}>\frac{\partial^2\hat{\omega}(J_t)}{\partial J_t\partial\lambda},$$

which holds under condition (2.14). □

Proof of Routine Displacement across Regions (equation (2.16))

Proof. The prove of routine displacement is analogous to machine displacement. That is, the first term from equation (2.10), is

$$\frac{\partial\left(\frac{\partial\ln L_{RT,t}}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{\partial J_t}=\frac{-\underline{x}(2J_t-\underline{x})}{J_t^2(J_t-\underline{x})^2}\frac{dJ_t}{d\ln(N_t)}+\frac{\underline{x}}{J_t(J_t-\underline{x})}\frac{d^2J_t}{d\ln(N_t)dJ_t}>0.$$

[1] Technically, this still holds for thresholds below $J^\star$, as long as the absolute value of the first term is larger than the second term.

The second effect is negative and the first is positive for all $J_t > J^\star$. From equation (2.12),

$$\frac{dJ_t}{d\lambda} > 0,$$

making the first term unambiguously positive. The direct effect on routine displacement is,

$$\frac{\partial\left(\frac{\partial \ln L_{RT,t}}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{\partial\lambda} = \frac{\underline{x}}{J_t(J_t-\underline{x})}\left(\frac{dJ_t}{d\ln(N_t)}\right)^2\left(-\frac{d^2\hat{\omega}(J_t)}{dJ_t d\lambda}\right).$$

The algebraic sign depends on the exact $\hat{\alpha}_\ell(i)$-slope. Collecting terms, for equation (2.16) to be positive, it must be that

$$\left[\left(\frac{(2J_t-\underline{x})}{J_t(J_t-\underline{x})}\right)+\left(\frac{d^2\hat{\omega}(J_t)}{dJ_t^2}+\frac{1-2J}{(J_t(1-J_t))^2}\right)\frac{dJ_t}{d\ln(N_t)}\right]\frac{1}{\hat{\alpha}_\ell(i)}\frac{d\hat{\alpha}_\ell(J_t)}{d\lambda} > \frac{d^2\hat{\omega}(J_t)}{dJ_t d\lambda},$$

which is always true under condition (2.14). $\square$

Proof of Low-Skilled Service Growth across Regions (equation (2.17))

Proof. The first term of equation (2.17) is,

$$\frac{\partial\left(\frac{\partial \ln L_{LST,t}}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{\partial J_t} = \frac{1}{J_t^2}\frac{dJ_t}{d\ln(N_t)} - \frac{1}{J_t}\frac{d^2J_t}{d\ln(N_t)dJ_t} < 0,$$

The first effect is negative and the second is positive for all $J_t > J^\star$. Since, from equation (2.12),

$$\frac{dJ_t}{d\lambda} > 0,$$

the first term of equation (2.17) is negative. The direct effect is,

$$\frac{\partial\left(\frac{\partial \ln L_{LST,t}}{\partial J_t}\frac{dJ_t}{d\ln(N_t)}\right)}{\partial\lambda} = -\frac{1}{J_t}\left(\frac{dJ_t}{d\ln(N_t)}\right)^2\left(-\frac{d^2\hat{\omega}(J_t)}{dJ_t d\lambda}\right).$$

The algebraic sign depends on the exact $\hat{\alpha}_\ell(i)$-slope. Collecting terms, for equation (2.17) to be negative, it must be that

$$\left[\left(\frac{1}{J_t}\right)+\left(\frac{d^2\hat{\omega}(J_t)}{dJ_t^2}+\frac{1-2J}{(J_t(1-J_t))^2}\right)\frac{dJ_t}{d\ln(N_t)}\right]\frac{1}{\hat{\alpha}_\ell(i)}\frac{d\hat{\alpha}_\ell(J_t)}{d\lambda} > \frac{d^2\hat{\omega}(J_t)}{dJ_t d\lambda},$$

which is always true under condition (2.14). $\square$

B.2 Data Appendix

For the analysis we have two main data sources. First, it is based on the factually anonymous dataset of the Sample of Integrated Labour Market Biographies - Regional File 1975-2008 (SIAB-R 7508), Nuremberg 2011. Specifically, we worked with a Scientific Use File, obtained from the The Research Data Centre (FDZ) of the Federal Employment Agency at the Institute for Employment Research. Second, we use the BIBB/IAB Qualification and Career Survey (QCS) 1979 and 1999. These surveys were conducted by the German Federal Institute for Vocational Training (BIBB) in conjunction with the Research Institute of the Federal Employment Agency (IAB).

B.2.1 The SIAB Regional File 1975-2008

The *SIAB Regional File 1975-2008* is a 2% random sample of the "Integrierte Erwerbsbiographien (IEB)" collected by the *Institute for Employment Research* (IAB) that is representative for the German workforce. It covers all currently employed individuals that are subject to social security payments for the years 1975 to 2008. It excludes self-employed, civil servants, individuals doing their military service and students. Marginally employed are only considered after 1999. It also covers current job seekers and benefit recipients, both are excluded for our analysis however. From there we extracted information on individuals' education, occupation, wages, region of work and personal characteristics.

B.2.1.1 Sample Selection and Variable Description

This Section summarizes sample selections regarding employment, education and wages.

Employment. The sample is restricted to males and females in West Germany. We drop individuals whose status of employment is coded as "doing an apprenticeship/traineeship", "doing an internship" or those that have an undefined employment status. When computing sampling weights we lack exact data on hours worked per individual. However, we have information on whether a worker works part-time and hence follow Dustmann *et al.* (2009) and weight part-time workers by 2/3.

Education. As in Dustmann *et al.* (2009) among others, our education variable is based on extrapolated data following imputation *method 1* in Fitzenberger *et al.* (2006). The high-skilled are defined as workers who graduated from university or college, while middle skill workers hold a high-school degree or an apprenticeship degree. All workers that enter the labor market without a high-school degree are defined as low-skilled. Apprentices are classified as individuals that obtained an apprenticeship degree within the same broad sector (of services or non-services) they currently work in.

Wages. When ranking occupations (see Figures 2.1a and 2.2a), we compute mean wages for each occupation in 1979. We only consider full-time workers for this. Since wages are top-coded, we follow the literature and impute censored wages by a fixed factor. Here we follow Dustmann *et al.* (2009) and use the imputation factor of 1.2, which fits the German data well according to the authors.

B.2.1.2 Descriptive Statistics

Table B.1 displays the descriptive statistics for main variables used in the empirical section plus several control variables. Specifically, it shows the (unweighted) mean and the standard deviation is given in parentheses. As expected, routine shares decreased over

Table B.1: Descriptive Statistics 1979 and 2008 across Regions

	1979	2007
RTI share	0.359 (0.061)	0.293 (0.055)
Routine Share	0.366 (0.064)	0.286 (0.061)
Manual Share	0.382 (0.055)	0.316 (0.056)
Abstract Share	0.340 (0.044)	0.427 (0.047)
PC Share		0.475[a] (0.044)
Service Share	0.420 (0.095)	0.602 (0.096)
Low Service Share	0.183 (0.029)	0.221 (0.029)
Apprentice Share	0.630 (0.043)	0.584 (0.033)
Female Share	0.363 (0.044)	0.443 (0.035)
Immigrant Share	0.072 (0.041)	0.060 (0.030)
Young Share	0.218 (0.038)	0.094 (0.016)
Age	37.1 (1.614)	42.5 (0.771)
Part-time Share	0.077 (0.020)	0.318 (0.036)

time, while abstract shares increased from 1979 to 2008. Manual tasks slightly decreased. The PC measure comes from the BiBB data and is for the year 1999 (see B.2.2.1 for details). The share of service sector employment increases, as well as the share of female workers.[2] At the same time, the share of workers in part-time occupations rose, which is highly related to female labor market participation. Average age increases due to the demographic transition. This, together with higher university attendance rates, then decreased the share of young workers (aged 25 and below) from 1979 to 2008 significantly.

[2] The low service share is computed using occupational information and following the definition of Blossfeld (1985).

Table B.2 shows changes in broad occupation employment shares over time.[3] As in the US, the middle of the skill distribution, "Production/Craft-occupation" has seen a fall. However, unlike the US the rise in "Services" has been small, and most of the fall in production has been absorbed by a rise in professional occupation employment shares. Using the same occupation classification, Table B.3 computes average task measures of

Table B.2: Employment Shares by Broad Occupation Class

	Employment Shares		Employment Changes	
Occupation Class	1979	2008	Δ_{79-08}	$Growth_{79-08}$
Managers	0.023	0.031	0.008	33.4%
(Semi-)Professionals	0.043	0.092	0.049	113.8%
Technicians/Engineers	0.069	0.074	0.006	8.1%
Commercial/Administration	0.261	0.302	0.042	16.0%
Production/Craft	0.411	0.267	-0.144	-35.0%
Agricultural occupations	0.010	0.012	0.001	14.0%
Services	0.183	0.222	0.038	20.9%

routine, manual and abstract tasks by occupation. The Table uses the US task measures, although as seen in the paper, the German and US task measures are similar. Again

Table B.3: Tasks by Broad Occupation Class

Occupation Class	*RTI*	Routine	Manual	Abstract
Managers	0.379	4.450	2.523	6.021
(Semi-)Professionals	0.358	4.318	3.051	6.125
Technicians/Engineers	0.408	5.105	3.852	5.451
Commercial/Administration	0.413	4.678	2.912	5.196
Production/Craft	0.477	6.433	5.903	4.091
Agricultural occupations	0.407	4.891	5.002	4.614
Services	0.438	5.197	4.532	4.380

in line with the theory, the occupations with the largest employment fall are the most routine-intensive occupations. The occupations with the largest increase are the most abstract occupations.

B.2.2 The Qualification and Career Survey

The QCS is a representative survey of employees carried out by the *BiBB* ("Federal Institute for Vocational Education and Training") and the *IAB* ("Institute for Employment Research"). It contains four cross-sections carried out in 1979, 1985/86, 1991/92 and

[3]The definition of broad occupation classes in Tables B.2 and B.3 follow the definition by Blossfeld (1985).

1998/99, where each covers about 30,000 individuals. The newest cross section was carried out in 2006 by the *BiBB* and the *BAuA* ("Federal Institute for Occupational Safety and Health"). Very similar to the four surveys before, the structure remained the same - however, the number of individuals interviewed reduced to 20,000. For our analysis we only make use of the 1979 and the 1999 waves. In particular, we these datasets to construct the computer utilization measures. In addition we can compute occupation-specific task measures from it (denoted by "BIBB"-measures in Section 2.3).

B.2.2.1 Computer Measure

People are asked whether they use personal computers (PCs) during their regular work. From this information we construct an occupation k specific PC measure as the average share of workers within each occupation that use a PC. Moreover, since PC usage varies extensively between different sectors, we differentiate between the broad sector of services and non-services (sector is denoted by s, occupation by k, individual by i):

$$PC^{99}_{sk,t=1999} = \left(\sum_{s=1}^{S}\sum_{i=1}^{I} L_{iskt} \cdot 1\left[PCuse_{iskt} = "YES"\right]\right)\left(\sum_{s=1}^{S}\sum_{i=1}^{I} L_{iskt}\right)^{-1}.$$

Using the *SIAB-R 7508* panel and using regional employment shares of each occupation in 1999 as weights, a weighted mean of PC usage within a region is computed. A region's j specific PC measure is,

$$PC^{99}_{j,t=1999} = \left(\sum_{s=1}^{S}\sum_{k=1}^{K} L_{jskt} \cdot PC^{99}_{sk,t=1999}\right)\left(\sum_{s=1}^{S}\sum_{k=1}^{K} L_{jskt}\right)^{-1}.$$

B.2.3 Further Datasources

Figure 2.1a for the US uses the 1980 and 2000 census. The sample includes all working individuals, that are not institutionalized, in school or in active-military duty. All observations are weighted by there US census weight multiplied by their annual hours worked.

B.3 Supplementary Appendix

B.3.1 The SIAB Regional File 1975-2008: Further Information

Table B.4 shows the distribution of skills for Germany as a whole in 1979 and 2008 respectively. Column (3) of the Table gives the change (in percentage points) over the 29-year time interval. As expected, in 1979 the share of high-skilled is very low, less than

Table B.4: Skill Shares within Germany between 1979-2008

Employment share	1979	2008	Δ_{79-08}
Highskilled	0.0479	0.1431	0.0951
Apprenticeshare	0.6325	0.5600	-0.0725

5 percent of the German workforce went to university or a technical college. 29 years later the share had almost tripled. Although the share of apprentices fell by 7 percentage points, it is still substantial.

Column(1) of Table B.5 shows the ten regions with the highest apprentice share (relative to their total workforce). Wolfsburg, Kassel and Nordhorn are the three regions that are most apprentice-intensive in 1979. This seems to be driven by the type of their industry structure, e.g. *Volkswagen* has its headquarter in Wolfsburg. Kassel has large automotive and (light) metal industries. It is also home to several armament industries. Nordhorn has a large consumer goods industry, e.g. textiles. Regions dominated by manufacturing industries are more prone to train and employ apprentices than the service sector. Column (2) shows the regions that are most intensive in routine jobs (using the compounded routine measure RTI). These cities seem to be rather heterogeneous in their characteristics, indicating that routine task shares can stem from different occupations. Routine tasks are either routine manual (dominant in industrial jobs) or routine cognitive tasks (found in clerk and sales occupations). Luedenscheid and Wolfsburg are industrial cities, while Balingen's largest employer is EDEKA (general partnership of supermarkets). Column (3) displays the regions with the highest employment share in abstract-intensive occupations. All cities are large cities and their industry structure shows that they tend to have a much larger service sector and less specialization in one specific industry.

Table B.6 shows the ten occupations with the lowest and highest mean wage in 1979. The mean daily wage of a full-time employee within that occupation is provided. Not very surprisingly, the lowest paid jobs would classify as low-skilled service jobs such as hairdressers, household cleaners or attending on guests. In contrast, scientists, engineers and entrepreneurs are at the top of the wage distribution. The daily wage rate shows

Table B.5: Regional Variation in Task Shares in 1979

The 10 most intensive regions in		
Apprentices	*RTI* Employment	Abstract Tasks
Wolfsburg	Balingen	Muenchen
Kassel	Kronach	Mainz
Nordhorn	Rottweil	Frankfurt/Main
Emden	Coburg	Hamburg
Leer	Schwandorf	Muenster
Heide	Wolfsburg	Goettingen
Itzehoe	Luedenscheid	Bonn
Hoexter	Weiden	Wiesbaden
Husum	Tuttlingen	Duesseldorf
Hersfeld	Dingolfing	Hannover

that the highest paid occupations earn more than three times as much as the low-skilled occupation.

Table B.6: Lowest and Highest Paying Occupations in 1979

Lowest Paying Jobs 1979		Highest Paying Jobs 1979	
Occupation	Wage	Occupation	Wage
Hairdresser	19.74	Scientists	72.28
Household cleaners	26.00	Physicians, pharmacists	71.79
Cutters	27.39	Mechanical,motor engineers	71.00
Attending on guests	27.62	(Land) Surveyor	70.34
Medical receptionists	27.64	Electrical engineers	69.53
Salespersons	28.16	Architects	66.55
Housekeeping managers	28.90	Entrepreneur, managing directors	66.45
Laundry workers	29.38	Economists, social scientists	64.28
Booksellers	31.49	Member of parliament	61.65
Agricultural workers	31.66	Data processing specialist	61.02

B.3.2 The Qualification and Career Survey: Further Information

B.3.2.1 Occupation Specific Tasks

To construct occupation-specific task intensities we use the 1979 survey, since these should reflect "initial" task requirements prior to computerization.[4]

To form task measures for each occupation that is specified in the *SIAB-R 7508* datafile, the 1979 QCS occupation classification can be matched to the official 1988 3-

[4]Compare Spitz-Oener (2006) for a detailed description of the dataset and evidence that task-requirements changed within occupations over time.

digit classification of the *German Federal Employment Bureau* (Bundesanstalt fuer Arbeit, 1988), which form the basis for the *SIAB-R 7508* regional file occupation classification.

The 1979 QCS covers 29,737 employees of German citizenship between the age of 15 to 65. Soldiers and the federal border guard are excluded. The individual's occupation is classified according to the 6-digit level based on the 1970 classification system. For our purpose, we define occupations on the 3-digit level (called "Berufsordnungen"). This is done for two reasons: (1) forming a representative task measure for each occupation requires information from a suitable number of employees within each occupation; and (2) the definition of an occupation has to be consistent over time.[5] After dropping unclassifiable occupations, 318 occupations and 28,459 individual observations are left. Similar to the US DOT measures, four measures are computed from the QCS,

1. *Routine task*: Routine intensity is measured by how often single work steps repeat themselves. The repetitiveness of jobs is classified from 1 to 5, i.e., from very repetitive to not at all.

2. *Manual task*: Manual task intensity is measured by the intensity of dexterity ("Handgeschick und Fingerfertigkeit") the job requires. It is measured on a scale from 1 to 5, from "(almost) always required" to "hardly any dexterity required."

3. *Non-routine interactive task*: Classified by the intensity of required planning and coordination skills. Measured on the scale 1 to 5, from very intense in coordination requirements to not at all.

4. *Non-routine analytic task*: Measured by the occupations' math requirements. Tasks are classified into five categories from very basic arithmetic operations to very advanced arithmetic knowledge including differential calculus, integrals and algebra.

Each task is re-classified on a scale from 1 to 10, with 10 being the highest task intensity.

Although the original *SIAB* dataset uses the official 1988 *Bundesanstalt fuer Arbeit, 1988* occupation classification, for the regional file these detailed differentiated occupations have been aggregated to a broader level. There are 120 occupations in the regional file. The *SIAB-R 7508* occupation-specific task measure is computed as the weighted mean of individual task measures from the QCS. Following Autor *et al.* (2003) we use full-time equivalent hours of labor supply as weights.[6]

[5] The 1979 datafile includes 12 occupations that cannot be matched to the classifications of the Bundesanstalt fuer Arbeit (1988). These are occupations wrongly coded or that have become obsolete.

[6] The full-time equivalent hours of labor supply are calculated as the product of sampling weights times weekly working working hours.

C Appendix: Chapter 3

C.1 Theoretical Appendix

C.1.1 Solution of the Laissez-Faire Equilibrium

In each country at each period t the intermediate good producer maximizes profits according to

$$max_{[x^i_{jt};L^i_{jt}]} \left\{ p^i_{jt} Y^i_{jt} - w^i_{jt} L^i_{jt} - \int_0^1 p^i_{jmt} x^i_{jmt} dm \right\}, \tag{C.1}$$

from where optimal demand for each machine jm, x^i_{jmt}, and demand for labor input, L^i_{jt} is found. For each intermediate machine jm one entrepreneur has access to the most efficient technology and thus will enjoy monopoly power. Let p^i_{jmt} denote the monopoly price charged by the entrepreneur. The maximization problem for an entrepreneur of machine m in sector j at time t reads as

$$\pi^i_{jmt} = (p^i_{jmt} - \psi) x^i_{jmt}.$$

Together with the iso-elastic demand function, the optimal price chosen by the monopolist of machine m in sector j at time t will be $p^i_{jmt} = \varphi/\alpha = \alpha$. That at hand, aggregate demand for each machine as given by

$$x^i_{jmt} = \left(p^i_{jt}\right)^{\frac{1}{1-\alpha}} L_{jt} A_{jmt}, \tag{C.2}$$

and monopoly's profits are as given in (3.12). Using the first order condition w.r.t. labor pins down wages for manufacturing labor as

$$w^i_{jt} = (1-\alpha) p^i_{jt} \left(L^i_{jt}\right)^{-\alpha} \left(A^i_{jt}\right)^{1-\alpha} \left(x^i_{jt}\right)^{\alpha}. \tag{C.3}$$

Observe that the wage in sector j increases in the price of this sectoral good, the stock of production technology and the amount of machine inputs. On the other hand due to diminishing returns, the more labor is working within the sector, the lower the wage.

Using x^i_{jmt} gives the relative wage as

$$\frac{w^i_{dt}}{w^i_{ct}} = \left(\frac{p^i_{dt}}{p^i_{ct}}\right)^{\frac{1}{1-\alpha}} \frac{A^i_{dt}}{A^i_{ct}}. \tag{C.4}$$

Now since the input factors are substitutes an increase in the relative knowledge of dirty production increases the wage in the dirty sector for $\sigma > 1$. However, since labor is mobile across sectors and labor markets have to clear, in equilibrium wages are equal across sectors, which implies

$$\frac{p^i_{dt}}{p^i_{ct}} = \left(\frac{A^i_{dt}}{A^i_{ct}}\right)^{-(1-\alpha)}. \tag{C.5}$$

Moreover sectoral output is given by

$$Y^i_{jt} = \left(p^i_{jt}\right)^{\frac{\alpha}{1-\alpha}} L^i_{jt} A^i_{jt}. \tag{C.6}$$

Combining (C.6) and (3.12) gives the relative prices as

$$\frac{p^i_{dt}}{p^i_{ct}} = \left(\frac{A^i_{dt} L^i_{dt}}{A^i_{ct} L^i_{ct}}\right)^{-\frac{1-\alpha}{\sigma}}, \tag{C.7}$$

and finally using (C.5) gives the relative labor inputs as

$$\frac{L^i_{dt}}{L^i_{ct}} = \left(\frac{A^i_{dt}}{A^i_{ct}}\right)^{\sigma-1}. \tag{C.8}$$

Whenever $\sigma > 1$ an increase in relative productivity draws labor to the same sector in order to offset the change in wages due to the productivity rise. $\sigma = \epsilon(1-\alpha) + \alpha > 0$ denotes the elasticity of substitution between factors. As long as intermediate goods are substitutes, the factors are substitutes as well and $\sigma > 1$.
Finally equilibrium aggregate output within country i at point t is given by

$$Y^i_t = \left[\left(A^i_{ct}\right)^{-(\sigma-1)} + \left(A^i_{dt}\right)^{-(\sigma-1)}\right]^{\frac{1}{\sigma-1}} A^i_{dt} A^i_{ct}. \tag{C.9}$$

Turning to pollution and utility, within both countries pollution increases at a positive rate. The growth rate of pollution is given by

$$g_p^N \approx \ln(P_{t+1}/P_t) = \ln\left(\frac{1+\gamma_d^N}{1+\delta_t^N}\right) = \ln\left(1+\gamma_d^N\right)^{\frac{1}{\phi}}, \tag{C.10}$$

$$g_p^S \approx \ln(P_{t+1}/P_t) = \ln\left(\frac{1+\gamma_d^N}{1+\delta_t^S}\right) = \ln\left[(1+\gamma_d^S)(1+\gamma_d^N)^{\frac{\delta}{\phi}}\right]^{\frac{1}{\delta+\phi}}, \tag{C.11}$$

using the specification for abatement techniques and pollution given. Not surprisingly, as the North grows at a faster rate, also pollution is increasing faster within the Northern countries. Global pollution then is rising at a strictly positive rate larger than g_p^S and smaller than g_p^N and utility approaches its lower bound.

$$g_p^G = \ln(P_{t+1}^N + P_{t+1}^S) - \ln(P_t^N + P_t^S), \tag{C.12}$$

$$U_t^i(C_t^i, P_t^G \to \infty) = -\infty. \tag{C.13}$$

Proof of Lemma 3.1

Equilibrium Allocation of scientists

Proof. Define the ratio of obtainable profits that governs the entrepreneurs' decision as a function of scientists s_{ct}^i working in the clean sector

$$f(s_{ct}^i) = \left(\frac{1+s_{ct}^i\gamma_c^i}{1+(1-s_{ct}^i)\gamma_d^i}\right)^{\sigma-2} \frac{1+\gamma_c^i}{1+\gamma_d^i}\left(\frac{A_{c,t-1}^i}{A_{d,t-1}^i}\right)^{\sigma-1}.$$

Depending on the substitutability between inputs in the two sectors: $\sigma = \epsilon(1-\alpha)+\alpha$, the expression is either strictly increasing (for $\sigma > 2$) or strictly decreasing (for $\sigma < 2$) in the number of workers in the clean sector s_{ct}^i.
Then for $s_{ct}^i \in [0,1]$ it is $\frac{\Pi_{ct}^i}{\Pi_{dt}^i} = f(s_{ct}^i)$. If $f(1) > 1$, clearly $s_{ct}^i = 1$ is an equilibrium, while for $f(0) < 1$ then $s_{ct}^i = 0$ is an equilibrium and finally for $f(s_{ct}^i) = 1$ with $0 < s_{ct}^i < 1$ then s_{ct}^i is an equilibrium.

1. If $\sigma < 2$ then $f(s_{ct}^i)$ is strictly decreasing in its argument. Thus it follows if
   - $f(1) > 1$ then $s_{ct}^i = 1$ is the unique equilibrium;
   - if $f(0) < 1$ then $s_{ct}^i = 0$ is the unique (corner) solution;
   - if $f(0) > 1 > f(1)$ then by continuity of the function there exists an interior solution such that $f(s_{ct}^i) = 1$.
2. If $\sigma > 2$ then $f(s_{ct}^i)$ is strictly increasing in its argument. It follows that

- if $1 < f(0) < f(1)$ then $s^i_{ct} = 1$ is the only equilibrium;
- if $f(0) < f(1) < 1$ then $s^i_{ct} = 0$ is the unique solution;
- if $f(0) < 1 < f(1)$ then there exist multiple equilibria: an interior solution such that $f(s^i_{ct}) = 1$, $s^i_{ct} = 0$ and $s^i_{ct} = 1$.

3. If $\sigma = 2$ then $f(s^i_{ct}) := f$ is constant in s^i_{ct}.Then if $f > 1$ $s^i_{ct} = 1$ is the equilibrium and if $f < 1$ then $s^i_{ct} = 0$ is the unique equilibrium.

□

Proof of Proposition 3.1

Proof. First, the parameter assumptions $(1+\gamma^i_c) < (1+\gamma^i_d)^{\frac{\sigma-1+\phi}{\phi(\sigma-1)}}$ ensure the existence of the dirty laissez-faire steady state. Note that this assumption is derived from the fact that the laissez-faire technology ratio is strictly smaller than the critical threshold, which would induce entrepreneurs to invest in clean technologies. Although this specific expression is derived from the North, it also ensures the existence of the equilibrium in the South.
In order to prove uniqueness of the dirty laissez-faire equilibrium, I show (i) Northern and Southern scientists all invest in the dirty technologies throughout and (ii) the form of technological progress is innovation in the North and imitation in the South. First, Assumption 1 together with Lemma 3.1 ensure that all entrepreneurs invest in dirty technologies in the first period. From (3.3) it is clear that $\frac{A^i_{c,t=1}}{A^i_{d,t=1}}$ decreased whenever $\frac{A^i_{c,t=0}}{A^i_{d,t=0}} > \left(\frac{A^i_c}{A^i_d}\right)^{LF}$, where $\left(\frac{A^i_c}{A^i_d}\right)^{LF}$ denotes the steady state technology ratio under the dirty regime. Clearly then, clean technologies will fall backwards even more. On the other hand, whenever $\frac{A^i_{c,t=0}}{A^i_{d,t=0}} < \left(\frac{A^i_c}{A^i_d}\right)^{LF}$, clean technologies rise initially. However, they will never exceed the steady state technology ratio, which guarantess a dirty investment strategy under the stated parameter conditions. Hence, all research investments are channeled into the dirty sector initially, throughout and in both countries. Second, under Assumption 2 the North constitutes the technological leader within both sectors and innovates in the first period. Since both countries invest in the same sector and $\gamma^N_d > \gamma^S_d$ the North must remain the technological leader throughout. □

C.1.2 Long-run Steady States under Environmental Regulation

Proof of Proposition 3.2

Proof. Existence and uniqueness of the equilibrium is trivial for the North: Assumption 4 gives the unique equilibrium distribution of scientists by construction and since $\gamma^S_d < \gamma^N_d$ it must be that the North remains the technological leader. For the South existence and uniqueness of the "dirty imitation equilibrium" requires $\frac{\Pi_c^{SS}}{\Pi_d^{SS}}(s_c^{SS} = 1) < 1$ since $\sigma > 2$. This is ensured by the given parameter condition in Proposition 3.2. $\square$

Proof of Proposition 3.3

Proof. Assumption 4 gives the unique equilibrium distribution of scientists for the North. The form of technical progress is not straight however since $\gamma_c^S < \gamma_c^N < \gamma_d^S$. (3.22) shows that $a_d^{SS} > a_c^{SS} > 1$ (for $\gamma_d^S > \gamma_c^N$) such that the South has overtaken the technological frontier and the Northern scientists imitate the clean technologies. Finally, existence and uniqueness of the "dirty innovation equilibrium" in the South requires $\frac{\Pi_c^{SS}}{\Pi_d^{SS}}(s_c^{SS} = 1) < 1$ since $\sigma > 2$. This is ensured by the given parameter condition in Proposition 3.3. $\square$

Proof of Proposition 3.4

Proof. The parameter condition in Proposition 3.4 ensures that it is optimal for all entrepreneurs to invest in the clean sector both within the North and the South. This ensures existence and together with Assumption 3 it ensures uniqueness of a "clean equilibrium" within both countries. Finally, since $\gamma_c^S < \gamma_c^N$ it must be that the North remains the technological leader throughout. $\square$

C.1.3 Transition and Dynamical Equations

The transitional dynamics will depend on relative technology ratios between countries as well as between sectors. The following Lemma summarizes the dynamical system in the most general way:

Lemma C.1. *Denoting the country-specific technology ratios as $AS_t := \frac{A_{ct}^S}{A_{dt}^S}$ and $AN_t := \frac{A_{ct}^N}{A_{dt}^N}$, the dynamics are described by the following equations:*

$$
\begin{aligned}
a_{dt} - a_{d,t-1} &= (1 + s_{dt}^S \gamma_d^S) a_{d,t-1}^{1-\delta-\phi} \left(\frac{A_{max,t-1}^S}{A_{max,t-1}^N} \right)^{\phi} - a_{d,t-1}, \\
a_{ct} - a_{c,t-1} &= \frac{1 + s_{ct}^S \gamma_c^S}{1 + \gamma_c^N} a_{c,t-1}^{1-\delta-\phi} \left(\frac{A_{max,t-1}^S}{A_{max,t-1}^N} \right)^{\phi} - a_{c,t-1}, \\
AN_t - AN_{t-1} &= (1 + \gamma_c^N) AN_{t-1}^{1-\delta-\phi} \left(\frac{\bar{A}_{c,t-1}}{\bar{A}_{d,t-1}} \right)^{\delta} \left(\frac{A_{max,t-1}^N}{A_{max,t-1}^N} \right)^{\phi} - AN_{t-1}, \\
AS_t - AS_{t-1} &= \frac{1 + s_{ct}^S \gamma_c^S}{1 + s_{dt}^S \gamma_d^S} AS_{t-1}^{1-\delta-\phi} \left(\frac{\bar{A}_{c,t-1}}{\bar{A}_{d,t-1}} \right)^{\delta} \left(\frac{A_{max,t-1}^S}{A_{max,t-1}^S} \right)^{\phi} - AS_{t-1},
\end{aligned}
$$

where $\delta = 0$ if $\{\exists\, j \in \{c,d\} : a_{jt} \geqslant 1\}$ and $\delta > 0$ otherwise.

Proof of Proposition 3.5

Proof. From Lemma C.1, and starting from a point, where there are only R&D investments in the dirty sector, $s^S_{c,t=0} = 0$, the derivation of AS_{trap} as given in equation (3.27) is straight forward. In fact, starting within the dirty equilibrium requires that $AS_{t=0} < \bar{k}$. Now, three different transitional paths are possible: first, if $AS_{t=0} < AS_{trap} < \bar{k}$, the relative stock of technologies rises along the transition but remains below the critical threshold value that would trigger a shift to clean technologies also for the South. Second, if $AS_{t=0} < \bar{k} < AS_{trap}$, again along the transitional path the ratio of clean technologies is increasing for the South. In contrast to the case before however, Southern entrepreneurs switch to investing in the clean sector as soon as $AS_t = \bar{k}$. Finally, whenever $AS_{trap} < AS_{t=0} < \bar{k}$, the ratio, AS_t, falls along the transitional path. In particular, the adjustment is instantaneously such that the ratio of clean technologies drops immediately, before rising again in conjunction with the Northern relative stock of clean technologies. Note that the equilibrium outcome depends on the exact parameter specification, but in either case is a unique long-run equilibrium. Finally, since $\gamma^S_d < \gamma^N_c$, the South will be imitating technologies, independent of the sector it invests in. □

Proof of Proposition 3.6

Proof. The first part of the proof resembles the proof of 3.5. Starting from a point, where $AS_{t=0} < \bar{k}$, the relative ratio of clean technologies will move towards AS_{trap}. Since, this value is the maximum long-run value of the Southern technology ratio, whenever $AS^{trap} < \bar{k}$, Southern entrepreneurs never switch to the clean sector. However, in contrast to before, since $\gamma^S_d > \gamma^N_c$, they will perform innovation and thus determine the growth rate of the world technological frontier. If $AS^{trap} > \bar{k}$, two possible scenarios can arise depending on the initial distance to the frontier for the Southern dirty sector, $a_{d,t=0}$. From the dynamical system in Lemma C.1, it is clear that as soon as the South overtakes the dirty technological frontier it starts innovation. Then the ratio of clean technologies, AS_t starts to decrease again, which makes the switch to the clean sector impossible. As innovation starts within the South, the channel of technological transfers across countries is shut down and the clean sector does not profit anymore from the expanding clean frontier defined by the North. Denote T^1 the number of periods the South needs to reach the dirty frontier (after the introduction of regulations in the North). Starting from the dirty regime, that is $A^S_{max,t-1} = A^N_{max,t-1} = A_{d,t-1}$, T^1 is implicitly defined by

$$\begin{aligned} a_{d,T^1} &= (1+\gamma^S_d) a^{(1-\delta)}_{d,T^1-1}, \\ a_{d,T^1} &= (1+\gamma^S_d)(1+\gamma^S_d)^{(1-\delta)} a^{(1-\delta)^2}_{d,T^1-2} \\ &\Rightarrow \\ 1 &= \left(1+\gamma^S_d\right)^{\sum_{(i=0)}^{(T^1-1)}(1-\delta)^i} a^{(1-\delta)^{T^1}}_{d,t=0}. \end{aligned}$$

Equivalently denote T^2 the number of periods it takes the ratio of technologies to reach the threshold value that induces a shift to clean technologies. Then T^2 is indirectly defined by:

$$\begin{aligned} AS_{T^2} &= \frac{1}{(1+\gamma^S_d)} AS^{1-\phi-\delta}_{T^2-1} AN^{\delta}_{T^2-1}, \\ AS_{T^2} &= \frac{1}{(1+\gamma^S_d)} \left(\frac{1}{(1+\gamma^S_d)}\right)^{1-\phi-\delta} AS^{(1-\phi-\delta)^2}_{T^2-2} \left((1+\gamma^N_c) AN^{1-\phi}_{T^2-2}\right)^{\delta} \\ &\Rightarrow \\ \bar{k} &= \left(1+\gamma^S_d\right)^{\sum_{(i=0)}^{(T^2-1)} -(1-\phi-\delta)^i} AS^{(1-\phi-\delta)^{T^2}}_{t=0} \left[\left(1+\gamma^N_c\right)^{\sum_{(i=0)}^{(T^2-2)}(1-\phi)^i} AN^{(1-\phi)^{(T^2-1)}}_{t=0}\right]^{\delta} \\ & \quad if \;\; T^2 > 1. \end{aligned}$$

and for $T^2 = 1$:

$$\bar{k} = \frac{1}{(1+\gamma^S_d)} AS^{1-\phi-\delta}_{t=0} AN^{\delta}_{t=0}.$$

Then, whenever $T^1 < T^2$, the dirty technological frontier will be reached first and the economy converges to the "dirty innovation equilibrium". If in turn, $T^1 > T^2$ the economy switches out of the dirty regime as soon as $AS_{trap} = \bar{k}$ and converges to the "clean imitation equilibrium". □

C.2 Data Appendix

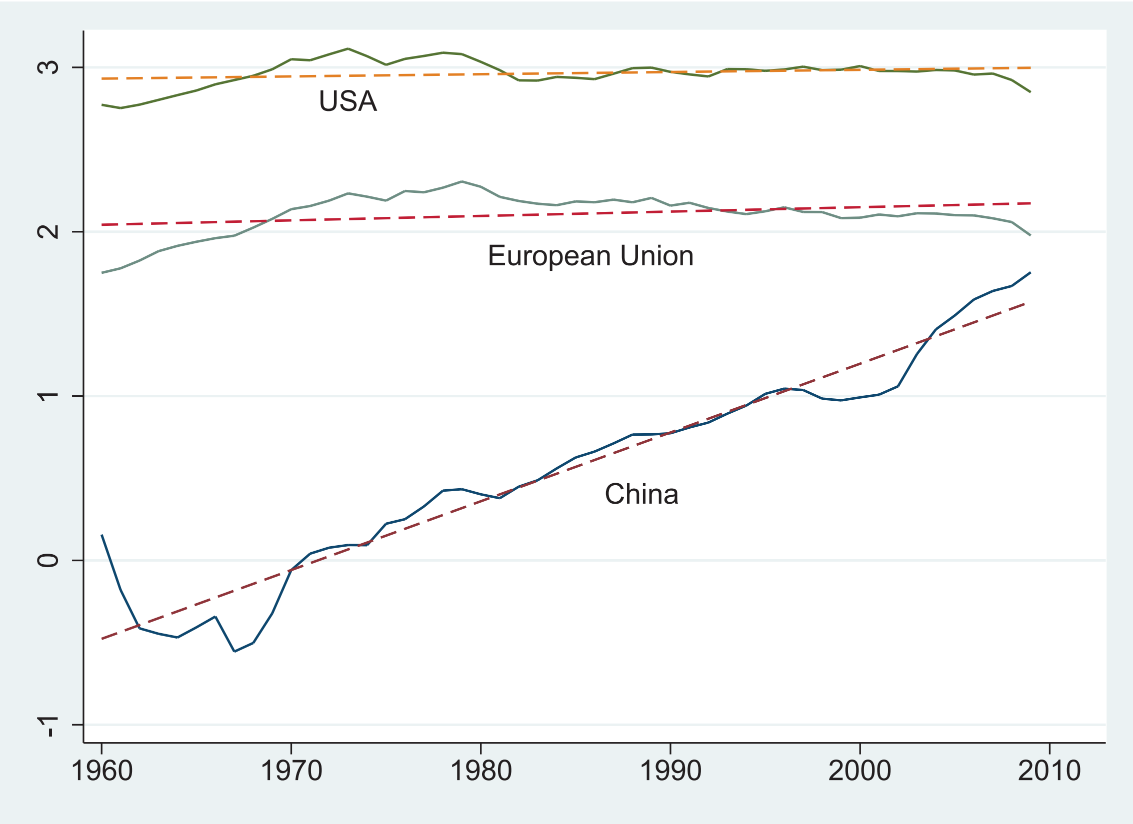


Figure C.1: Evolution of CO2 Emissions per capita

Notes: The figure shows the per capita CO2 emissions on a log-scale for China, the European Union and the US. While levels are still lower in emerging markets, they are growing at a rapid rate. The slope coefficients are given by 0.042 (0.002), 0.003 (0.001) and 0.001 (0.001) respectively.
Source: worldbank.org (database)

D Appendix: Chapter 4

D.1 Data Appendix

D.1.1 Market Size & CHNS

Definition of Income Groups

Household income and household income per capita is provided by the CHNS in longitudinal data-files including the latest wave 2009.[1] Household disposable income in the CHNS is conceptualised as the sum of all sources of market and non-market incomes or revenues minus expenses on the household or individual level. We use houehold income deflated to constant 2009 Yuan, using the price deflator provided by the CHNS (2012a,b) which is based on a standard NBS consumer basket allowing for price differences between urban and rural areas.
We split the income distribution into $g = 1, ..., G$ groups setting fixed income thresholds in constant 2009 Yuan and calculate the population share $i_{g,t}$ of each income group g for each survey year t.

In our baseline, we take inspiration from the World Bank's (WB, 2009) classification of countries[2] and divide households into four ($G = 4$) income groups: low income, lower middle income, upper middle income and high income. To account for sampling artifacts in the 2006 survey, we project household incomes per capita between 1997 and 2009 using the growth rate of average household income per capita in this period. The World Bank's thresholds in constant 2009 dollars and were converted into constant 2009 yuan. All dollar figures where converted into constant 2009 Yuan using the exchange rate and PPP adjustment factors.[3] To account for the small number of observations in early waves

[1]See Beerli (2010) for a more detailed description.

[2]The World Bank (2009) classifies economies according to their 2009 GNI per capita, calculated using the World Bank Atlas method. The following thresholds are set: low income, US \$ 995 or less; lower middle income, US \$ 996 - US \$ 3'945; upper middle income, US \$ 3'946 - US \$ 12'196; and high income, US \$ 12'196 or more.

[3]Dollar values are converted to constant 2009 using the China Version 2 exchange rate and PPP adjustment factor from the Penn World Tables 7.0, i.e. $threshold \times \frac{XRAT}{PPP}$. With some adjustments to account for small sampling of high income groups, this yields the following thresholds in constant 2009 Yuan: low income (2'149 Yuan), lower middle income (2'150 - 8'514 Yuan), upper middle income (8'515 - 16'499 Yuan), high income (16'500 or more).

in some higher income groups, we slightly adjusted these thresholds with the largest adjustment for the threshold of the high income group.[4]

Usage Profiles and Base-Year

The choice of a base-year for ownership profiles implies different assumptions about entrepreneurs expectations, on the one hand, and accuracy considerations on the other hand. Taking ownership profiles from a survey year at the beginning of our panel, e.g 1997, we assume that entrepreneurs base their expectations about ownership profiles on durable good prices and qualities from 1997. As Beerli (2010) shows in his analysis of durable good ownership between 1989 and 2006, depending on the durable good, ownership rates were generally increasing across the income distribution mainly explained by a substantial fall in durable goods prices but also by improvements in public service provision and other factors. Additionally, ownership rates increased unevenly across the income distribution with poor households gaining much more from price changes compared to richer income groups. This implies that the aggregate, potential ownership stocks based on the year 1997 will underestimate the true market size substantially. With respect to accuracy, picking 1997 as a base-year involves the problem that there are relatively few rich households (i.e. less than 1%) which makes the information about their ownership profiles relatively inaccurate.[5] Taking the latest survey year available, i.e. 2009, on the other hand, assumes that entrepreneurs form their expectations (about the future development of durable good sales) based on durable good prices and qualities from 2009. Since ownership rates generally increased over time, our potential ownership stock measure based on the year 2009 overestimates the true market size. Yet, since there are many more rich households in 2009 than in earlier years, their ownership profile should be estimated more accurately. Thus, independently from the choice of the base-year, potential stocks will be either over- or underestimated. Moreover, it means that potential sales, the difference between two years, will generally be lower than actual sales.[6]

Population Measure Implications

In the CHNS we observe a household's ownership and change in ownership status of a specific durable good variety j and without having information on its price and quality.

[4] The adjusted thresholds are: low income, US \$ 2'149, low middle income, US \$ 2'150 -US \$US 4'167, high middle income, US \$ 4'168 - US \$ 8'075, high income, US \$ 8'076 or more.

[5] Another problem is that some durable goods become available only in later survey years, e.g. cellphones from 2004.

[6] This is in line with the findings of Beerli (2010) who finds that the share of changes in aggregate ownership explained by income can differ substantially between different durable goods, being only 31% for color TVs.

Dealing with such a population measure of market size has some implications.[7] First, we can not distinguish between a car acquisition of one household to another household on a quality or price dimension[8]. All acquisition within the same durable good variety j receive the same (population) weight.[9] Thus, we think of the new car acquisition, which we observe in the CHNS, as an average car bought or a count measure of sales whose magnitude can only be compared across durable goods. Second and related, we can not distinguish between sales values of similar magnitude between different durable goods. A 1 percentage point sale of cars and a 1 percentage point sale of bicycles affects their respective industries with a similar magnitude although an average car differs from an average bicycle to a large extent in value terms.

D.1.2 Construction of Total Factor Productivity at the Firm-level

To construct a measure of firm-level productivity we follow an estimation procedure suggested by Levinsohn and Petrin (2003). They propose taking intermediate inputs as a proxy for unobserved shocks affecting a firm's input choice instead of investment as suggested by Olley and Pakes (1996). One advantage of this approach is strictly data driven as investment is zero for many firms in our dataset whereas intermediate inputs are not. As Levinsohn and Petrin (2003) show, taking investment as proxy for unobserved productivity shocks is only valid for firms reporting non-zero investment. We use the STATA implementation `levpet` to estimate the parameters of the production function:

$$y_{i,t} = \beta_0 + \beta_l l_{i,t} + \beta_k k_{i,t} + \beta_m m_{i,t} + \omega_{i,t} + \eta_{i,t}$$

using the logarithm of real intermediate inputs, $m_{i,t}$, as proxy variable. $y_{i,t}$ denotes the logarithm of real value-added of firm i in year t, $l_{i,t}$ denotes the logarithm of the number of workers, $k_{i,t}$ the logarithm of the real capital stock, $\omega_{i,t}$ represents the unobserved productivity component and $\eta_{i,t}$ is an error term that is uncorrelated with input choices. The real capital stock variable was constructed following a procedure suggested by Brandt *et al.* (2011). Nominal values of value-added and the capital stock measure were deflated using the input- and output-deflators provided by Brandt *et al.* (2011).

The estimation yields $\hat{\beta}_l = 0.176$ and $\hat{\beta}_k = 0.36$. According to Levinsohn and Petrin (2003), estimated productivity for firm i at time t is then given by

[7]Note that Acemoglu and Linn (2004) use a similar population measure of drugs used in a certain age group.

[8]This also includes second hand markets.

[9]Note that also acquisitions across time cannot be distinguished, although a car bought in 1989 and one bought in 2009 might, technically speaking, be a very different durable good.

$$\hat{\omega}_{i,t} = \exp\left(y_{i,t} - \hat{\beta}_l l_{i,t} - \hat{\beta}_k k_{i,t}\right).$$

D.1.3 Tables

Table D.1: Table: Service Life and Depreciation Rates of Durable Goods

Durablegood	Service Life L_j	Category in BEA (2003)
air condition	11	other household appliances
camera	10	photographic equipment
car	8	other motor vehicles
cellphone	9	computer and peripheral equipment
computer	9	computer and peripheral equipment
cycles	10	wheel goods
electric fan	10	other durable house furnishings
refrigerator	11	kitchen and other household appliances
homevideo appliances	9	video and audio products
kitchen appliances	11	kitchen and other household appliances
motorcycle	8	other motor vehicles
radio	9	video and audio products
satellite dish	10	other durable house furnishings
sewing machine	10	other durable house furnishings
telephone	10	other durable house furnishings
washing machine	11	kitchen and other household appliances

Notes: Source: BEA (2003).

Table D.2: Usage Profiles, $u_{j,g}$, of Income Groups According to WB (2009) Classification, Base-year 2009

	Usage intesity in income group (Increase in usage intensity from lower group)				
Durable Good	**Low**	**Low Middle**	**High Middle**	**High**	**Income Group with Largest Increase**
air condition	0.054	0.075	0.154	0.311	
		(0.021)	(0.079)	(0.157)	high
camera	0.013	0.021	0.058	0.132	
		(0.008)	(0.036)	(0.074)	high
car	0.009	0.013	0.020	0.046	
		(0.004)	(0.007)	(0.026)	high
cellphone	0.283	0.372	0.508	0.642	
		(0.089)	(0.136)	(0.133)	high middle
computer	0.030	0.048	0.099	0.192	
		(0.019)	(0.051)	(0.092)	high
cycles	0.176	0.236	0.319	0.347	
		(0.060)	(0.083)	(0.028)	high middle
electric fan	0.390	0.487	0.580	0.646	
		(0.096)	(0.093)	(0.066)	low middle
fridge	0.124	0.148	0.255	0.336	
		(0.024)	(0.106)	(0.081)	high middle
homevideo	0.316	0.364	0.463	0.561	
		(0.048)	(0.100)	(0.097)	high middle
kitchen appliances	0.338	0.423	0.618	0.832	
		(0.084)	(0.195)	(0.214)	high
motorcycle	0.076	0.111	0.117	0.107	
		(0.035)	(0.006)	(-0.009)	low middle
radio	0.039	0.056	0.112	0.161	
		(0.017)	(0.056)	(0.048)	high middle
sat_dish	0.029	0.035	0.029	0.040	
		(0.006)	(-0.006)	(0.011)	high
sewingm	0.073	0.077	0.110	0.120	
		(0.004)	(0.033)	(0.010)	high middle
telephone	0.107	0.142	0.228	0.304	
		(0.035)	(0.086)	(0.076)	high middle
washing	0.159	0.180	0.258	0.336	
		(0.021)	(0.078)	(0.078)	high middle

Notes: All data are from CHNS, wave 2009. Households are grouped according to household income per capita in constant in constant 2009 Yuan: low income (2'149 Yuan), lower middle income (2'150 - 8'514 Yuan), upper middle income (8'515 - 16'499 Yuan), high income (16'500 or more). The first row of each durable good shows usage intensities (the $\bar{u}_{j,g} = u_{j,g,t=2009}$s), i.e. the average number of goods per capita, and the second row shows the increase in the usage intensity (in brackets) moving from the income group below into the income group of that column.

Table D.3: Correspondence between CHNS Durable Good Categories and ASIP Industries

Durable Good in CHNS	**Industry Name in CIC**	**CIC pre 2003**	**CIC post 2003**	**Industry in Analysis**
air condition	Home air conditioner manufacturers	4065	3952	air condition
bicycle	Bicycle manufacturers	3740	3741	cycles
camera	Camera and equipment manufacturing	4254	4153	camera
car	Automobile manufactoring	3721-3725	3721	car
cellphone	Mobile communications and terminal equipment manufacturing	-	4014	cellphone
colour TV	Home video equipment manufacturing	4171	4071	homevideo appliances
computer	Computer machine manufacturing	4141	4041	computer
dvd	Home video equipment manufacturing	4171	4071	homevideo appliances
electric fan	Manufacturers of household electrical appliances ventilation	4064	3953	electric fan
refrigerator	Household refrigerating appliances manufacturing	4063	3951	refrigerator
microwave	Household kitchen appliances manufacturing	4066	3954	kitchen appliances
motorcycle	Motorcycle manufacturing	3731	3731	motorcycle
presscooker	Household kitchen appliances with manufacturing	4066	3954	kitchen appliances
radio	Home audio equipment manufacturing	4172	4072	radio
ricecooker	Household kitchen appliances manufacturing	4066	3954	kitchen appliances
satellite dish	Radio and television receiving equipment manufacturing	4130	4032	satellite dish
sewing machine	Sewing machinery manufacturing	3674	3653	sewing machine
telephone	Communication terminal equipment manufacturing	4113	4013	telephone
tricycle	Bicycle manufacturing	3740	3741	cycles
washing machine	Household cleaning electrical appliances manufacturing	4061, 4062	3955	washing machine

Table D.4: Summary Statistics

Variable	Mean	Std. dev.	Min.	Max.	# Observations
$\ln TFP_{i,j,t}$	5.245	1.150	1.440	10.643	30883
$\ln Laborproductivity_{i,j,t}$	4.025	1.141	-1.214	9.694	30883
$\ln MS^{actual}_{j,t,t+4}$	16.918	0.974	14.630	18.543	111
$\ln MS^{potential}_{j,t,t+4}$	16.879	0.927	14.869	18.274	123
$SIZE_{i,j,t}$	5.437	1.309	2.079	12.145	30883
$1(FOE_{i,j,t} = 1)$	0.375	0.484	0	1	30883
$1(SOE_{i,j,t} = 1)$	0.072	0.259	0	1	30883
$1(COE_{i,j,t} = 1)$	0.268	0.443	0	1	30883
$1(DPE_{i,j,t} = 1)$	0.281	0.449	0	1	30883
$1(AGE_{i,j,t} > \overline{AGE})$	0.535	0.498	0	1	30876
$1(COAST_{i,j,t} = 1)$	0.845	0.361	0	1	30883
$HHI_{j,t}$	568.085	459.197	99.2	2863.28	30883
$1(EXP_{i,j,t} > 0)$	0.491	0.499	0	1	30866
$TECHPOT_{j,t}$	2.618	0.521	1.111	4	155

Notes: $\ln TFP_{i,j,t}$ denotes log of total factor productivity of firm i in industry j and year t, estimated as described in Appendix D.1.2. $\ln Laborproductivity_{i,j,t}$ is measured as the log of firm's value added over its number of employees. $SIZE_{i,j,t}$ the log of number of workers. $\ln MS^{actual}_{j,t,t+4}$ and $\ln MS^{potential}_{j,t,t+4}$ are actual and potential market size measured in log-terms, respectively and over a five year time horizon as described in the text. $1(FOE_{i,j,t} = 1)$, $1(SOE_{i,j,t} = 1)$, $1(COE_{i,j,t} = 1)$ and $1(DPE_{i,j,t} = 1)$ indicate whether a firm is foreign owned, state owned, collectively owned or a domestic private enterprise, respectively. $1(AGE_{i,j,t} > \overline{AGE})$ indicated whether a firm is above the median age of all firms in the sample. $1(COAST_{i,j,t} = 1)$ is a dummy for whether a firm is located in a coastal province. $HHI_{j,t}$ is the Hirschmann-Herfindahl index as described in the text. $1(EXP_{i,j,t} > 0)$ is a dummy for whether a firm has positive export sales and $TECHPOT_{j,t}$ is the world wide technology potential assessed by Swiss firms in the KOF Innovation Survey. Data is based on the 10% trimmed sample (see Section 4.2.2).

Table D.5: Summary Statistics at Industry Level (part I)

		$\ln TFP_{i,j,t}$		$\ln Investment_{i,j,t}$		$\ln Laborproductivity_{i,j,t}$		$\ln MS^{actual}_{j,t,t+4}$		$\ln MS^{potential}_{j,t,t+4}$		$SIZE_{i,j,t}$	
Industry	# Observations	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
aircond	1936	5.319	1.167	7.607	2.460	4.344	1.071	16.795	0.294	16.814	0.199	5.354	1.281
camera	851	5.246	1.120	7.529	2.515	3.848	1.122	15.789	0.045	15.891	0.241	5.714	1.282
car	3156	5.349	1.431	8.555	2.923	4.036	1.399	14.978	0.264	15.094	0.173	6.160	1.521
cellphone	1019	6.179	1.325	8.470	2.461	4.864	1.347	18.478	0.091	18.173	0.032	5.682	1.418
computer	1317	5.943	1.474	8.157	2.940	4.748	1.353	16.221	0.456	16.478	0.187	5.659	1.659
cycles	4052	4.839	0.825	6.519	2.030	3.748	0.878	17.213	0.178	17.505	0.063	5.035	1.025
electric fan	1504	4.999	0.943	7.091	2.168	3.843	0.938	18.157	0.046	18.147	0.047	5.299	1.199
fridge	1087	5.205	1.154	7.725	2.509	4.198	1.057	17.115	0.215	17.200	0.120	5.437	1.412
homevideo	2397	5.708	1.302	7.691	2.477	4.094	1.255	18.151	0.069	18.008	0.066	5.836	1.358
kitchenappl	2160	5.066	0.854	6.996	2.241	4.057	0.898	18.178	0.110	18.129	0.101	5.036	1.188
motorcycle	1974	5.481	1.106	7.730	2.323	4.316	1.063	16.828	0.056	16.746	0.011	5.430	1.193
radio	3191	5.126	0.967	6.682	2.394	3.576	0.993	15.966	0.470	16.510	0.145	5.580	1.209
satellite dish	1313	5.048	0.901	6.571	2.062	3.855	0.968			15.331	0.020	4.988	1.055
sewingm	2026	4.828	0.827	6.867	2.034	3.788	0.902	16.145	0.286	16.422	0.072	4.999	0.938
telephone	1581	5.370	1.178	7.422	2.433	4.085	1.314	17.319	0.333	17.177	0.110	5.465	1.342
washing	1319	5.088	0.995	7.467	2.163	4.135	0.989	17.244	0.108	17.247	0.095	5.305	1.144
All industries	30883	5.244	1.150	7.352	2.475	4.025	1.141	16.918	0.974	16.879	0.927	5.437	1.309

Notes: $\ln TFP_{i,j,t}$ denotes log of total factor productivity of firm i in industry j and year t, estimated as described in Appendix D.1.2. $\ln Investment_{i,j,t}$ is the yearly difference of a firm's fixed assets in logs. $\ln Laborproductivity_{i,j,t}$ is measured as the log of firm's value added over its number of employees. $SIZE_{i,j,t}$ is defined as the log of number of workers. $\ln MS^{actual}_{j,t,t+4}$ and $\ln MS^{potential}_{j,t,t+4}$ are actual and potential market size measured in logs, respectively, over a five year time horizon as described in the text. Data is based on the 10% trimmed sample (see Section 4.2.2).

Table D.6: Summary Statistics at Industry Level (part 2)

	$1(FOE_{i,j,t}=1)$		$1(SOE_{i,j,t}=1)$		$1(COE_{i,j,t}=1)$		$1(DPE_{i,j,t}=1)$		$1(AGE_{i,j,t}>\overline{AGE})$		$1(COAST_{i,j,t}=1)$		$HHI_{j,t}$	
Industry	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
aircond	0.396	0.489	0.024	0.152	0.320	0.467	0.259	0.438	0.553	0.497	0.847	0.360	955.92	304.01
camera	0.757	0.429	0.067	0.250	0.086	0.280	0.089	0.285	0.541	0.499	0.919	0.273	854.45	191.25
car	0.176	0.381	0.307	0.461	0.427	0.495	0.085	0.279	0.645	0.479	0.529	0.499	524.65	112.68
cellphone	0.608	0.488	0.024	0.152	0.166	0.372	0.200	0.400	0.421	0.494	0.831	0.375	1145.34	243.33
computer	0.501	0.500	0.092	0.289	0.260	0.439	0.146	0.353	0.450	0.498	0.764	0.425	643.06	305.23
cycles	0.380	0.485	0.030	0.172	0.234	0.424	0.354	0.478	0.580	0.494	0.954	0.209	144.98	41.24
electric fan	0.242	0.428	0.029	0.169	0.358	0.480	0.364	0.481	0.557	0.497	0.958	0.200	644.09	630.87
fridge	0.240	0.427	0.055	0.228	0.389	0.488	0.314	0.464	0.529	0.499	0.760	0.427	1564.42	621.97
homevideo	0.527	0.499	0.064	0.245	0.226	0.418	0.181	0.385	0.477	0.500	0.873	0.333	428.43	220.59
kitchenappl	0.299	0.458	0.004	0.064	0.207	0.406	0.489	0.500	0.443	0.497	0.977	0.149	922.35	407.41
motorcycle	0.130	0.336	0.082	0.275	0.367	0.482	0.419	0.494	0.456	0.498	0.710	0.454	376.56	43.65
radio	0.598	0.490	0.027	0.162	0.155	0.362	0.219	0.414	0.547	0.498	0.961	0.193	299.80	125.98
satellite dish	0.361	0.480	0.058	0.234	0.202	0.402	0.379	0.485	0.538	0.499	0.805	0.396	368.70	103.78
sewingm	0.226	0.418	0.041	0.199	0.299	0.458	0.434	0.496	0.551	0.498	0.914	0.281	353.68	97.26
telephone	0.474	0.499	0.118	0.323	0.237	0.425	0.168	0.374	0.592	0.492	0.806	0.396	888.87	795.26
washing	0.318	0.466	0.025	0.156	0.293	0.455	0.363	0.481	0.528	0.499	0.903	0.296	541.85	165.44
All industries	0.375	0.484	0.072	0.259	0.269	0.443	0.282	0.450	0.536	0.499	0.846	0.361	568.09	459.20

Notes: $1(FOE_{i,j,t}=1)$, $1(SOE_{i,j,t}=1)$, $1(COE_{i,j,t}=1)$ and $1(DPE_{i,j,t}=1)$ indicate whether a firm is foreign owned, state owned, collectively owned or a domestic private enterprise, respectively. $1(AGE_{i,j,t}>\overline{AGE})$ indicated whether a firm is above the median age of all firms in the sample. $1(COAST_{i,j,t}=1)$ is a dummy for whether a firm is located in a coastal province. $HHI_{j,t}$ is the Hirschmann-Herfindahl index as described in the text. Data is based on the 10% trimmed sample (see Section 4.2.2).

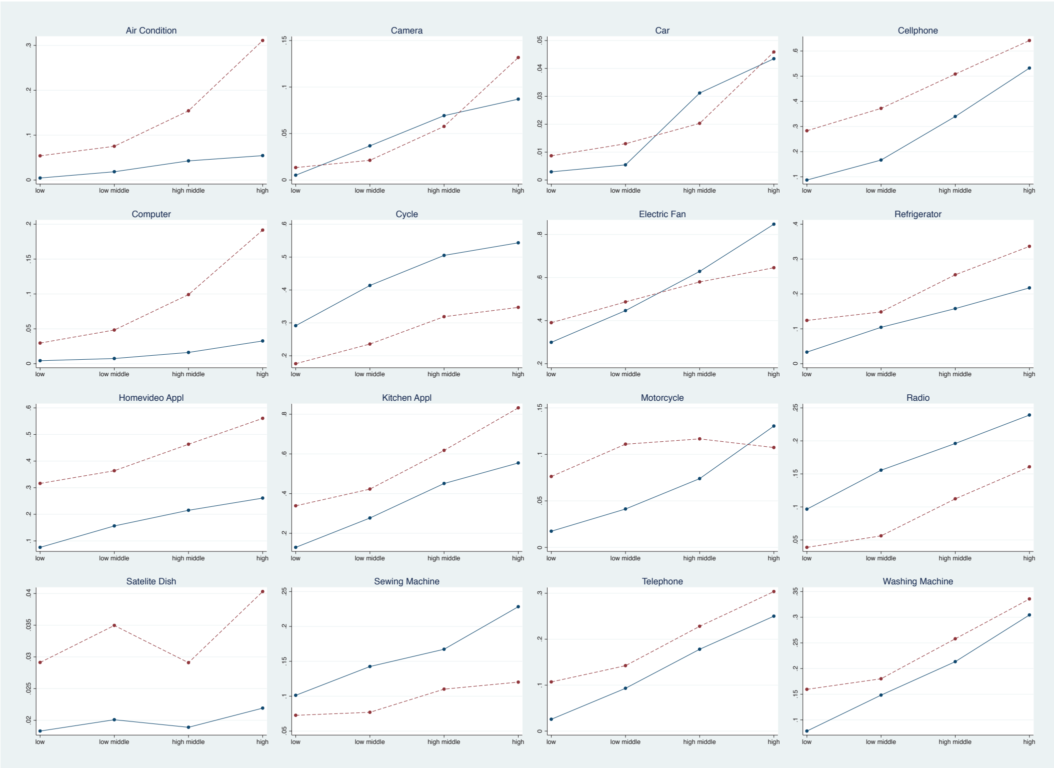
Table D.7: Summary Statistics at Industry Level (part 3)

	$1(EXP_{i,j,t} > 0)$		$EXPSH_{i,j,t}$		$TECHPOT_{j,t}$	
Industry	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
aircond	0.380	0.486	0.149	0.292	2.566	0.353
camera	0.763	0.426	0.604	0.429	2.488	0.333
car	0.214	0.410	0.019	0.096	2.827	0.093
cellphone	0.517	0.500	0.280	0.381	2.368	0.127
computer	0.411	0.492	0.280	0.421	3.466	0.380
cycles	0.539	0.499	0.331	0.409	2.570	1.113
electric fan	0.493	0.500	0.352	0.430	2.566	0.353
fridge	0.392	0.488	0.134	0.269	2.566	0.353
homevideo	0.605	0.489	0.412	0.433	2.440	0.115
kitchenappl	0.529	0.499	0.359	0.427	2.566	0.353
motorcycle	0.391	0.488	0.134	0.258	2.570	1.113
radio	0.691	0.462	0.578	0.450	2.574	0.440
satellite dish	0.497	0.500	0.339	0.418	2.440	0.115
sewingm	0.496	0.500	0.237	0.330	2.754	0.013
telephone	0.462	0.499	0.302	0.414	2.440	0.115
washing	0.559	0.497	0.271	0.370	2.566	0.353
All industries	0.491	0.500	0.297	0.404	2.618	0.522

Notes: $1(EXP_{i,j,t} > 0)$ is a dummy for whether a firm has positive export sales and $EXPSH_{i,j,t}$ is the share of export sales on total sales of a firm. $TECHPOT_{j,t}$ is the world wide technology potential assessed by Swiss firms in the KOF Innovation Survey. Data is based on the 10% trimmed sample (see Section 4.2.2).

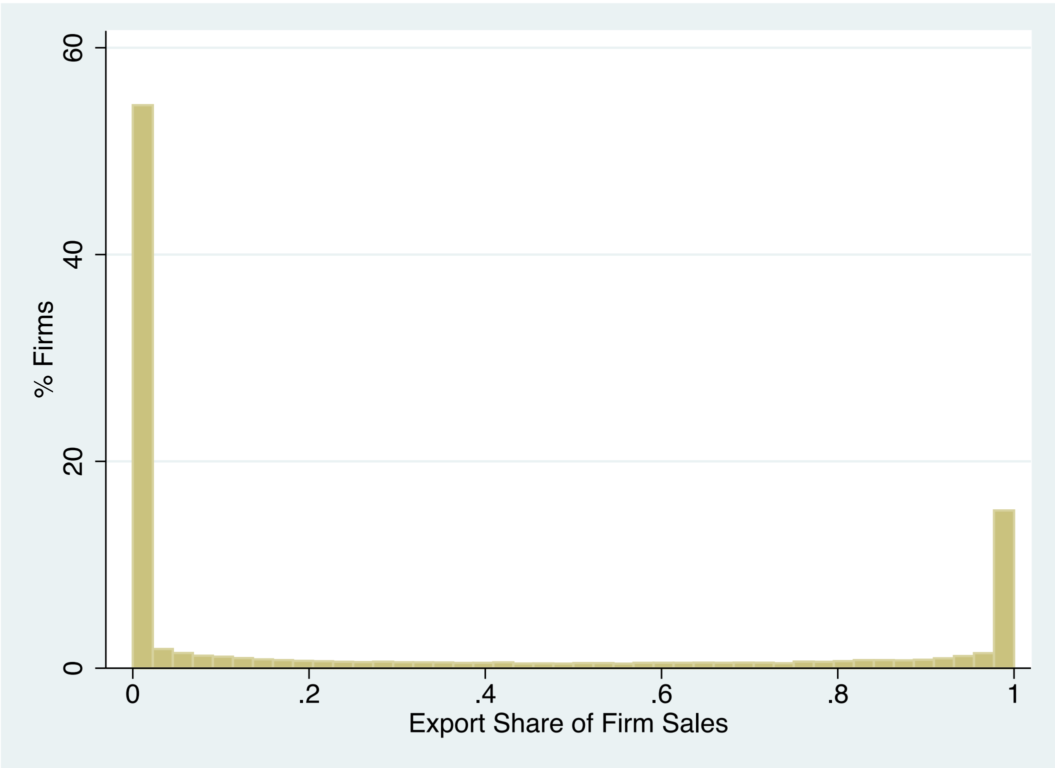
D.1.4 Figures

Figure D.1: Dynamic in Usage Intensities for Given Income Groups



Notes: CHNS data. Usage per head on the y-axis (different scales), the four income groups on the x-axis in ascending order. The solid line represents the usage profile, $u_{j,g,t}$, in the first survey period available before our analysis period. For most goods this is 1997 whereas it is 2004 for cellphones and 2006 for satellite dishes. The dashed line represents the usage profile for the latest wave available in the CHNS. For most goods this is 2009 whereas it is 2006 for radios. Income groups are defined as described in Section 4.3.2.

Figure D.2: Share of Firms Engaging in Exports



Notes: The figure plots the number of firms (in percentage terms) as a function of the export share relative to total firm sales. Data is based on the 10% trimmed sample (see Section 4.2.2). Source: ASIP dataset.

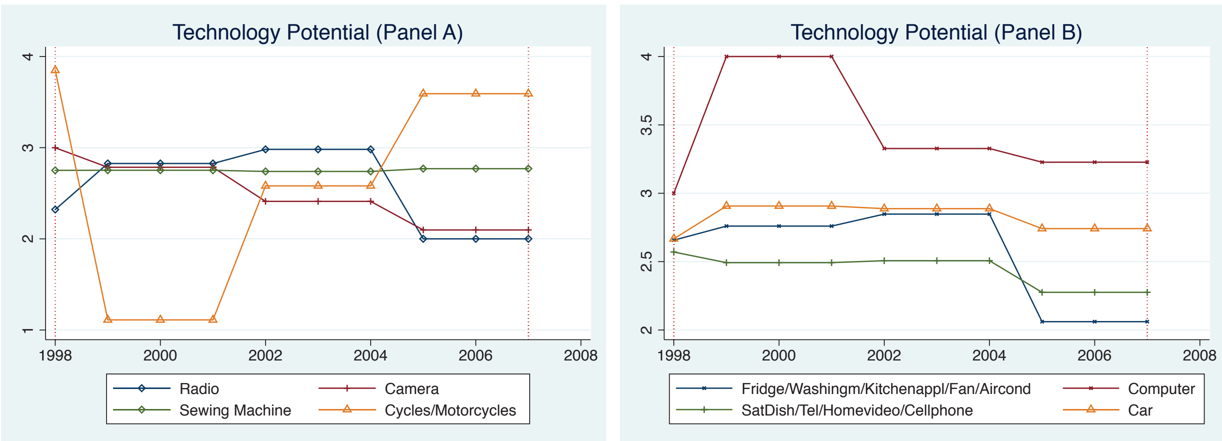


Figure D.3: Dynamic of Technology Potential

Notes: KOF Innovation Survey matched to ASIP data.

D.2 Empirical Appendix

Further Regressions

Table D.8: Effect of Market Size on LN TFP including Controls

Dep. Variable	$\ln TFP_{i,j,t}$					
Mean	5.137	5.137	5.137	5.137	5.137	5.137
St.Dev.	1.161	1.161	1.161	1.161	1.161	1.161
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln MS^{actual}_{j,t,t+4}$	0.188	0.0628	0.0628	0.549	0.272	0.272
	[0.0813]**	[0.0525]	[0.0395]	[0.185]***	[0.132]**	[0.0828]***
Size		0.346	0.346		0.344	0.344
		[0.0135]***	[0.0112]***		[0.0133]***	[0.0113]***
Admin_FE		0.134	0.134		0.132	0.132
		[0.0277]***	[0.0270]***		[0.0274]***	[0.0270]***
Admin_SOE		-0.741	-0.741		-0.740	-0.740
		[0.0373]***	[0.0523]***		[0.0370]***	[0.0523]***
Admin_COE		0.0351	0.0351		0.0313	0.0313
		[0.0219]	[0.0256]		[0.0222]	[0.0257]
Age		-0.237	-0.237		-0.236	-0.236
		[0.0177]***	[0.0193]***		[0.0174]***	[0.0193]***
Region		0.0410	0.0410		0.0414	0.0414
		[0.0281]	[0.0366]		[0.0286]	[0.0366]
HHI		1.60e-05	1.60e-05		6.36e-06	6.36e-06
		[2.15e-05]	[2.30e-05]		[2.69e-05]	[2.33e-05]
Method	OLS	OLS	OLS	2SLS	2SLS	2SLS
Observations	20,167	20,160	20,160	20,167	20,160	20,160
R^2	0.111	0.278	0.278	0.106	0.277	0.277
Clustering	Industry x Year	Industry x Year	Firm	Industry x Year	Industry x Year	Firm
No of Clusters				111	111	7662
F-Stats				27.68	26.70	1480

Notes: *** p<0.01, ** p<0.05, * p<0.1 denote significance on the 10%, 5% and 1% level, respectively. Observations below the 10 percentile of value-added each year are excluded. All columns include year and industry fixed effects. $\ln MS^{actual}_{j,t,t+4}$ is instrumented with $\ln MS^{potential}_{j,t,t+4}$.

Table D.9: Robustness Analysis: Controlling for Exports and Technology Supply Shocks

Dep. Variable	$\ln TFP_{i,j,t}$					
Mean	5.137	5.138	4.957	5.355	5.137	5.138
St. Dev.	1.161	1.160	1.102	1.191	1.161	1.160
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln MS^{actual}_{j,t,t+4}$	0.272	0.274	0.408	-0.164	0.265	0.267
	[0.132]**	[0.133]**	[0.141]***	[0.169]	[0.135]**	[0.136]**
$1(EXP_{i,j,t} > 0)$		0.0539				0.0540
		[0.0274]**				[0.0274]**
$TECHPOT_{j,t}$					-0.00541	-0.00558
					[0.0236]	[0.0240]
Sample	All	All	Non-Exporters	Exporters	All	All
Method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Observations	20,160	20,147	10,980	9,167	20,160	20,147
R^2	0.277	0.277	0.206	0.368	0.277	0.277
F-Stats	26.70	26.88	42.25	15.87	21.17	21.31

Notes: *** p<0.01, ** p<0.05, * p<0.1 denote significance on the 10%, 5% and 1% level, respectively. Robust standard errors (clustered on the industry-year level jt) are given in parentheses. Observations below the 10 percentile of value-added each year are excluded. All columns include year and industry fixed effects as well as a set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). $1(EXP_{i,j,t} > 0)$ is one if a firm has positive export sales. $\ln MS^{actual}_{j,t,t+4}$ is instrumented with $\ln MS^{potential}_{j,t,t+4}$. $TECHPOT_{j,t}$ is the world wide technology potential assessed by Swiss firms in the KOF Innovation Survey.

First Stage Regressions

Table D.10: First Stage Regression including Controls

Dep. Variable	$\ln MS^{actual}_{j,t,t+4}$		
	(1)	(2)	(3)
$\ln MS^{potential}_{j,t,t+4}$	1.967	1.955	1.955
	[0.374]***	[0.378]***	[0.0508]***
Size		0.00529	0.00529
		[0.00136]***	[0.00135]***
Admin_FE		-0.00228	-0.00228
		[0.00414]	[0.00431]
Admin_SOE		-0.00329	-0.00329
		[0.00607]	[0.00775]
Admin_COE		-0.00435	-0.00435
		[0.00576]	[0.00435]
Age		-0.00276	-0.00276
		[0.00572]	[0.00364]
Region		-0.000619	-0.000619
		[0.00432]	[0.00458]
HHI		1.75e-05	1.75e-05
		[6.05e-05]	[6.47e-06]***
Observations	20,167	20,160	20,160
R^2	0.968	0.968	0.968
Clustering	Industry x Year	Industry x Year	Firm
No of Clusters	111	111	7662
F-Stats	27.68	26.70	1480

Notes: *** p<0.01, ** p<0.05, * p<0.1 denote significance on the 10%, 5% and 1% level, respectively. Observations below the 10 percentile of value-added each year are excluded. All columns include year and industry fixed effects. The reported R^2 reported equals the partial R^2.

Table D.11: First Stage Regression - Trimming

Dep. Variable	$\ln MS^{actual}_{j,t,t+4}$				
	(1)	(2)	(3)	(4)	(5)
$\ln MS^{potential}_{j,t,t+4}$	1.990	1.970	1.955	1.951	1.907
	[0.381]***	[0.380]***	[0.378]***	[0.374]***	[0.358]***
Observations	22,328	21,241	20,160	16,900	11,412
R^2	0.244	0.241	0.239	0.241	0.247
Trimming	10%	0%	5%	25%	50%
No of Clusters	111	111	111	111	111
F-Stats	27.32	26.95	26.70	27.27	28.41

Notes: *** p<0.01, ** p<0.05, * p<0.1 denote significance on the 10%, 5% and 1% level, respectively. Robust standard errors (clustred on the industry-year level jt) are given in parentheses. All columns include year and industry fixed effects as well as a set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). The reported R^2 reported equals the partial R^2.

Table D.12: Robustness Analysis: First Stage Regression

Dep. Variable	$\ln MS^{actual}_{j,t,t+4}$ $\ln MS^{actual}_{j,t,t+4} \times 1(EXP_{i,j,t} > 0)$				
	(1)	(2)	(3)	(4)	(5)
$\ln MS^{potential}_{j,t,t+4}$	1.955	1.957	1.956	1.951	1.954
	[0.378]***	[0.378]***	[0.375]***	[0.424]***	[0.423]***
$\ln MS^{potential}_{j,t,t+4} \times 1(EXP_{i,j,t} > 0)$			-0.0217		
			[0.00584]***		
$1(EXP_{i,j,t} > 0)$	No	Yes	Yes	No	Yes
$TECHPOT_{j,t}$	No	No	No	Yes	Yes
Observations	20,160	20,147	20,147	20,160	20,147
R^2	0.239	0.240	0.248	0.223	0.223
R^2_2			0.885		
F-Stats	26.70	26.88		21.17	21.31
F-Stats1			40.31		
F-Stats2		839.5			

Notes: *** p<0.01, ** p<0.05, * p<0.1 denote significance on the 10%, 5% and 1% level, respectively. Robust standard errors (clustered on the industry-year level jt) are given in parentheses. Observations below the 10 percentile of value-added each year are excluded. All columns include year and industry fixed effects as well as a set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). The reported R^2 reported equals the partial R^2. In Column (3) F-Stats1 and the R^2 are on the first stage of $\ln MS^{potential}_{j,t,t+4}$, and F-Stats2 and R^2_2 are w.r.t. $\ln MS^{potential}_{j,t,t+4} \times 1(EXP_{i,j,t} > 0)$.

Table D.13: Robustness Analysis: First Stage Regression

Dep. Variable	$\ln MS^{actual}_{j,t,t+4}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln MS^{potential}_{j,t,t+4}$	1.955	1.957	1.559	2.258	1.951	1.954
	[0.378]***	[0.378]***	[0.391]***	[0.347]***	[0.424]***	[0.423]***
$1(EXP_{i,j,t} > 0)$	No	Yes	-	-	No	Yes
$TECHPOT_{j,t}$	No	No	No	No	Yes	Yes
Sample	All	All	Exporters	Non-Exporters	All	All
Observations	20,160	20,147	9,167	10,980	20,160	20,147
R^2	0.239	0.240	0.152	0.335	0.223	0.223
F-Stats	26.70	26.88	15.87	42.25	21.17	21.31

Notes: *** p<0.01, ** p<0.05, * p<0.1 denote significance on the 10%, 5% and 1% level, respectively. Robust standard errors (clustered on the industry-year level jt) are given in parentheses. Observations below the 10 percentile of value-added each year are excluded. All columns include year and industry fixed effects as well as a set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). The reported R^2 reported equals the partial R^2.

Table D.14: First Stage Regression - LN Laborprod

Dep. Variable	$\ln MS^{actual}_{j,t,t+4}$		
	(1)	(2)	(3)
$\ln MS^{potential}_{j,t,t+4}$	1.955	1.955	1.954
	[0.378]***	[0.0508]***	[0.423]***
Observations	20,160	20,160	20,147
R^2	0.239	0.239	0.223
Clustering	Industry x Year	Firm	Industry x Year
No of Clusters	111	7662	111
F-Stats	26.70	1480	21.31

Notes: *** p<0.01, ** p<0.05, * p<0.1 denote significance on the 10%, 5% and 1% level, respectively. Observations below the 10 percentile of value-added each year are excluded. All columns include year and industry fixed effects and a set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). Column (4) in addition introduces a dummy for positive exports, $1(EXP_{i,j,t} > 0)$ and the supply side control, $TECHPOT_{j,t}$. The reported R^2 reported equals the partial R^2.

Table D.15: First Stage Regression on the Industry Level

Dep. Variable	$\ln MS^{actual}_{j,t,t+4}$	
	(1)	(2)
$\ln MS^{potential}_{j,t,t+4}$	1.224	1.590
	[0.448]***	[0.407]***
$1(EXP_{i,j,t} > 0)$	No	Yes
$TECHPOT_{j,t}$	No	Yes
Observations	111	111
R^2	0.08	0.12
Observations	111	111
F-Stats	7.459	15.25

Notes: *** p<0.01, ** p<0.05, * p<0.1 denote significance on the 10%, 5% and 1% level, respectively. Robust standard errors are given in parentheses. Observations below the 10 percentile of value-added each year are excluded. All columns include year and industry fixed effects as well as the industry mean of the set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). Regressions are weighted by the number of firms within a sector. The reported R^2 reported equals the partial R^2.

Part IV

Bibliography

Bibliography

Acemoglu, D. (1998), "Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality," *Quarterly Journal of Economics*, 113(4), 1055-1089.

Acemoglu, D.and Pischke, J.S. (1998), "Why Do Firms Train? Theory and Evidence," *Quarterly Journal of Economics*, 113(1), 78-118.

Acemoglu, D. and Zilibotti, F. (2001), "Productivity Differences," *Quarterly Journal of Economics*, 116(2), 563-606.

Acemoglu, D. (2002), "Directed Technological Change," *Review of Economic Studies*, 69(4), 781-809.

Acemoglu, D. and Linn, J. (2004), "Market Size and Innovation: Theory and Evidence from the Pharmaceutical Industry," *Quarterly Journal of Economics*, 119(8), 1049-1090.

Acemoglu, D., Aghion, P. and Zilibotti, F. (2006), "Distance to Frontier, Selection and Economic Growth," *Journal of the European Economic Association*, 4(1), 37-74.

Acemoglu, D., Cutler, D., Finkelstein, A. and Linn, J. (2006), "Did Medicare Induce Pharmaceutical Innovation?," *American Economic Review*, 96(2), 103-107.

Acemoglu, D. (2009), *Modern Economic Growth*, Princeton, New Jersey: Princeton University Press.

Acemoglu, D., Aghion, P., Griffith, R. and Zilibotti, F. (2010), "Vertical Integration and Technology: Theory and Evidence," *Journal of the European Economic Association*, 8(5), 989-1033.

Acemoglu, D. and Autor, D. (2011), "Skills, Tasks and Technologies: Implications for Employment and Earnings," Handbook of Labor Economics, Vol.4., Ch.12, 1043-1171.

Acemoglu, D., Aghion, P., Bursztyn, L. and Hemous, D. (2012), "The Environment and Directed Technological Change," *American Economic Review*, 102(1), 131-166.

Adda, J., Dustmann, C., Meghir, C., and Robin, J.M. (2006), "Career Progression and Formal versus On-the-Job Training", IZA Discussion Papers 2260, Institute for the Study of Labor (IZA).

Aghion, P., Dechezlepretre, A., Hemous, D., Martin, R. and van Reenen, J. (2011), "Carbon Taxes, Path Dependency and Directed Technical Change: Evidence from the Auto Industry," CEP Discussion Paper CEPDP1178.

Angrist, J. and Pischke, J.S. (2009), *Mostly Harmless Econometrics: An Empiricist's Companion.* Princeton, New Jersey: Princeton University Press.

Antonczyk, D., DeLeire, T., and Fitzenberger, B. (2010), "Polarization and Rising Wage Inequality: Comparing the U.S. and Germany," IZA Discussion Papers 4842, Institute for the Study of Labor (IZA).

Arnold, J.M. and Hussinger, K. (2005), "Export Behaviour and Firm Productivity in German Manufacturing: A Firm-Level Analysis," *Review of World Economics*, 141(2), 219-243.

Arvanitis, S., Bolli, T., Hollenstein, H., Ley, M. and Wörter, M. (2010), "Starke Position der Schweizer Wirtschaft im Internationalen Innovationswettbewerb." KOF Analysen, Zürich: 79-89.

Autor, D., Katz, L.F., and Krueger, A.B. (1998), "Computing Inequality: Have Computers Changed The Labor Market?," *Quarterly Journal of Economics*, 113(4), 1169-1213.

Autor, D., Levy, F. and Murnane, R.J. (2003), "The Skill Content of Recent Technological Change: An Empirical Exploration," *Quarterly Journal of Economics*, 118(4), 1279-1333.

Autor, D. and Dorn, D. (2013), "The Growth of Low-Skill Service Jobs and the Polarization of the U.S. Labor Market," *American Economic Review*, 103(5), 1553-1597.

Baumol, W. (1967), "Macroeconomics of Unbalanced Growth: The Anatomy of Urban Crisis," *American Economic Review*, 57(3), 415-426.

Beerli, A. (2010), "The Evolution of Durable Goods Demand During China's Transition - An Empirical Analysis of Household Survey Data from 1989 to 2006," IPCDP Working Paper 201.

Benjamin, D., Brandt, L. and Giles, J. (2005), "The Evolution of Income Inequality in Rural China," *Economic Development and Cultural Change*, 53(4), 769-824.

Benjamin, D., Brandt, L., Giles, J. and Wang, S. (2005b), "Income Inequality During China's Economic Transition," in *China's Great Economic Transformation*, ed. Loren Brandt Thomas G. and Rawski, 729-775. Cambridge, Massachusetts: Cambridge University Press.

BiBB (1977), *Berufsbildungsbericht 1977*, Bunderminister für Bildung und Wirtschaft, Bonn.

BiBB (2011), *Berufsbildungsbericht 2011*, Bunderministerium für Bildung und Wirtschaft (BMBF), Bonn.

Bloom, N., Sadun, R. and Van Reenen, J. (2012), "Americans Do IT Better: US Multinationals and the Productivity Miracle," *American Economic Review*, 102(1), 167-201.

Blossfeld, H.P. (1985), *Bildungsexpansion und Berufschancen: Empirische Analysen zur Lage der Berufsanfaenger in der Bundesrepublik*, Frankfurt: Campus Verlag.

Blume-Kohout, M.E. and Sood, N. (2012), "Market Size and Innovation: Effects of Medicare Part D on Pharmaceutical Research and Development," *Journal of Public Economics*, 97, 327-36.

Boppart, T. (2011), "Structural Change and the Kaldor Facts in a Growth Model with Relative Price Effects and Non-Gorman Preferences," University of Zurich, Department of Economics Working Paper 2.

Boppart, T. and Weiss, F.J. (2013), "Non-Homthetic Preferences and Industry Directed Technical Change," University of Zurich, Department of Economics Working Paper 123.

Brandt, L., v. Biesenbroeck, J. and Zhang, Y. (2011), "Creative Accounting or Creative Destruction? Firm-Level Productivity Growth in Chinese Manufacturing," *Journal of Development Economics*, 97(2), 339-351.

Brock, W.A. and Taylor, M.S. (2003), "The Kindergarten Rule of Sustainable Growth," NBER Working Paper 9597.

Brock, W.A. and Taylor, M.S. (2010), "The Green Solow Model," *Journal of Economic Growth*, 15(2), 127-153.

Browning, M. (2008), "Engel's Law," in *The New Palgrave Dictionary of Economics, Second Edition*, ed. Steven N. Durlauf and Lawrence E. Blume, Palgrave Macmillan.

Bundesanstalt für Arbeit (1988), *Klassifizierung der Berufe 1988, Technical Report.*

Bureau of Economic Analysis (BEA), U.S. Department of Commerce (2003), "Fixed Assets and Consumer Durable Goods in the United States, 1925 - 1999," Washington, DC.

Bureau of Economic Analysis (BEA), U.S. Department of Commerce (2009), "Concepts and Methods of the U.S. National Input-Output Accounts," Ch.1-12, Washington, DC.

Bureau of Economic Analysis (BEA), U.S. Department of Commerce (2011), "Concepts and Methods of the U.S. National Income and Product Accounts," Ch.1-9, Washington, DC.

Casey, B. (1991), "Recent Developments in the German Apprenticeship System," *British Journal of Industrial Relations*, 29(2), 205-222.

Cotterill, R.W. (1986), "Market Power and the Retail Food Industry: Evidence from Vermont," *Review of Economics and Statistics*, 68(3), 379-386.

Crépon, B., Duguet, E. and Mairesse, J. (1998), "Research, Innovation and Productivity: An Econometric Analysis at the Firm Level," *Economics of Innovation and New Technology*, 7(2), 115-158.

De Mouzon, O., Dubois, P., Scott-Morton, F. and Seabright, P. (2011), "Market Size and Pharmaceutical Innovation," CEPR Discussion Paper DP8367.

Di Maria, C. and Smulders, S. (2004), "Trade Pessimists vs. Technology Optimists: Induced Technological Change and Pollution Havens," *Advances in Economic Analysis & Policy*, 3(2).

Dorner, M., Koenig, M., and Seth, S. (2011), "Sample of Integrated Labour Market Biographies. Regional file 1975-2008 (SIAB-R 7508)", FDZ Datenreport. Documentation on Labour Market Data 2011 07, Institute for Employment Research, Nuremberg, Germany.

Draca, M., Sadun, R. and Van Reenen, J. (2006), "Productivity and ICT: A Review of the Evidence," CEP Discussion Paper 749.

Dustmann, C. and Pereira, S.C. (2008), "Wage Growth and Job Mobility in the United Kingdom and Germany," *Industrial and Labor Relations Review*, 61(3), 374-393.

Dustmann, C., Ludsteck, J., and Schoenberg, U. (2009), "Revisiting the German Wage Structure," *Quarterly Journal of Economics*, 124(2), 843ñ881.

Eckey, H.F. (1988), "Abgrenzung Regionaler Arbeitsmärkte", *Raumforschung und Raumordnung*, 1(2), 24-33.

Eckey, H.F. and Klemmer, P. (1991), "Neuabgrenzung von Arbeitsmarktregionen fuer die Zwecke der Regionalen Wirtschaftspolitik," *Informationen zur Raumentwicklung*, 9(10), 569-577.

Engel, E. (1857), "Die Productions- und Consumptionsverhaeltnisse des Koenigsreichs Sachsen," *Zeitschrift des Statistischen Bureaus des Königlich Sächsischen Ministeriums des Inneren*, 8, 9.

EUKLEMS consortium (2007), "EU KLEMS Growth and Productivity Accounts, Part I Methodology," Version 1.0, prepared by Timmer, M. , van Moergastel, T., Stuivenwold, E., Ypma, G. and O'Mahony, M. and Kangasniemi, M..

EUKLEMS consortium (2007), "EU KLEMS Growth and Productivity Accounts, Part II Sources by Country," Version 1.0, prepared by Timmer, M. , van Moergastel, T., Stuivenwold, E., Ypma, G. and O'Mahony, M. and Kangasniemi, M..

Fang, M., Chan, Ch. and Yao, X. (2009), "Managing Air Quality in a rapidly developing nation: China," *Atmospheric Environment*, 43(1), 79-86.

Farrell, J. and Shapiro, C. (1990), "Asset Ownership and Market Structure in Oligopoly," *RAND Journal of Economics*, 21(2), 275-292.

Farrell, J. and Shapiro, C. (1990), "Horizontal Mergers: An Equilibrium Analysis," *American Economic Review*, 80(1), 107-126.

Feenstra, R., Li, Z. and Yu, M. (2011), "Exports and Credit Constraints under Incomplete Information: Theory and Evidence from China," NBER Working Paper 16940.

Finkelstein, A. (2004), "Static and Dynamic Effects of Health Policy: Evidence from the Vaccine Industry," *Quarterly Journal of Economics*, 119(2) 527-564.

Fitzenberger, B., Osikominu, A., and Voelter, R. (2006), "Imputation Rules to Improve the Education Variable in the IAB Employment Subsample," *Schmollers Jahrbuch: Journal of Applied Social Science Studies / Zeitschrift fuer Wirtschafts- und Sozialwissenschaften*, 126(3), 405-436.

Foellmi, R. and Zweimüller, J. (2006), "Income Distribution and Demand-Induced Innovations," *Review of Economic Studies*, 73(4), 941- 960.

Gao, J, and Jefferson, G. (2007), "Science and Technology Take-off in China? Sources of Rising R&D Intensity," *Asia Pacific Business Review*, 13(3), 357-371.

Goldin, C.D. and Katz, L.F. (2008), *The Race between Education and Technology.* Cambridge, Massachusetts: Belknap Press of Harvard University Press.

Goos, M., Manning, A., and Salomons, A. (2011), "Explaining Job Polarization: The Roles of Technology, Offshoring and Institutions," Technical Report, Katholieke Universiteit Leuven.

Gradus, R. and Smulders, S. (1993), "The Trade-off Between Environmental Care and Long-term Growth - Pollution in Three Prototype Growth Models," *Journal of Economics*, 58(1), 25-51.

Griliches, Z. and Schmookler, J. (1963), "Inventing and Maximizing," *American Economic Review*, 53(4), 725-729.

Hall, B.H., Jaffe, A.B. and Trajtenberg, M. (2001), "The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools," NBER Working Paper 8498.

Hanushek, E.A., Woessmann, L., and Zhang, L. (2011), "General Education, Vocational Education, and Labor-Market Outcomes over the Life-Cycle," NBER Working Paper 17504.

Harhoff, D. and Kane, T.J. (1993), "Financing Apprenticeship Training: Evidence from Germany," NBER Working Paper 4557.

Hemous, D. (2012), "Environmental Policy and Directed Technical Change in a Global Economy: is There a Case for Carbon Tariffs?," Harvard University Working Paper.

Herrendorf, B., Rogerson R. and Valentinyi, A. (2009), "Two Perspectives on Preferences and Structural Transformation," NBER Working Paper 15416.

Herrendorf, B., Rogerson R. and Valentinyi, A. (2011), "Growth and Structural Transformation." Manuscript, Princeton University. Forthcoming in *The Handbook of Economic Growth.*

Heston, A., Summers, R. and Aten, B. (2011), "Penn World Table Version 7.1." Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania.

Houthakker, H.S. (1957), "An International Comparison of Household Patterns, Commemorating the Century of Engel's Law," *Econometrica*, 25(4), 532-551.

Hsieh, Ch. and Klenow, P. (2009), "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economics*, 74(4), 1403-1448.

Hu, A. and Jefferson, G. (2008) "A Great Wall of Patents: What is Behind China's Recent Patent Explosion?," *Journal of Development Economics*, 90(1), 57-68.

IEA (2011), "World Energy Outlook 2011, Executive Summary."

Kaldor, N. (1961), "Capital Accumulation and Economic Growth," in *The Theory of Capital: Proceedings of a Conference of the International Economic Association*, ed. Friedrich A. Lutz and Douglas C. Hague. London: Macmillan.

Kohn, K. (2006), "Rising Wage Dispersion, After All! The German Wage Structure at the Turn of the Century," ZEW Discussion Papers 06-31, ZEW - Center for European Economic Research.

Koller, M. and Schwengler, B. (2000), "Struktur und Entwicklung von Arbeitsmarkt und Einkommen in den Regionen," in *Beiträge zur Arbeitsmarkt- und Berufsforschung*, 232. Nuremberg: Inst. für Arbeitsmarkt- und Berufsforschung der Bundesanstalt für Arbeit.

Krueger, D. and Kumar, K.B. (2004), "Skill-Specific rather than General Education: A Reason for US-Europe Growth Differences?," *Journal of Economic Growth*, 9(2), 167-207.

Kuznets, S. (1973), "Modern Economic Growth: Findings and Reflections," *American Economic Review*, 63(3), 247-258.

Levinsohn, J. and Petrin, A. (2003), "Estimating Production Functions Using Inputs to Control for Unobservables," *Review of Economic Studies*, 70(2), 317-341.

Liu, H. (2008), "The China Health and Nutrition Survey: An Important Database for Poverty and Inequality Research," *Journal of Economic Inequality*, 6(4), 373-376.

Mairesse, J. and Mohnen, P. (2010), "Using Innovations Surveys for Econometric Analysis," NBER Working Paper 15857.

Manning, A. (2004), "We Can Work It Out: The Impact of Technological Change on the Demand for Low-Skill Workers," *Scottish Journal of Political Economy*, 51(5), 581-608.

Mazzolari, F. and Ragusa, G. (2013), "Spillovers from High-Skill Consumption to Low-Skill Labor Markets," *Review of Economics and Statistics*, 95(1), 74-86.

Michaels, G., Natraj, A., and Reenen, J.V. (2010), "Has ICT Polarized Skill Demand? Evidence from Eleven Countries over 25 years," NBER Working Papers 16138.

Muellbauer, J. (1975), "Aggregation, Income Distribution and Consumer Demand," *Review of Economic Studies*, 42(4), 525-543.

Muellbauer, J. (1976), "Community Preferences and the Representative Consumer," *Econometrica*, 44(5), 979-999.

Newell, R., Jaffe, A. and Stavins, R. (1999), "The Induced Innovation Hypothesis and Energy-Saving Technological Change," *Quarterly Journal of Economics*, 114(3), 941-975.

Ngai, R. and Pissarides, C. (2007), "Structural Change in a Multi-Sector Model of Growth," *American Economic Review*, 97(1), 429-443.

Ngai, R. and Samaniego, R.M. (2011), "Accounting for Research and Productivity Growth across Industries," *Review of Economic Dynamics*, 14(3), 475-495.

Nordhaus, W.D. (2007), "Two Centuries of Productivity Growth in Computing," *Journal of Economic History*, 67(1), 128-159.

OECD (2013), "OECD Science, Technology and Industry Scoreboard 2013," Paris.

Olley, G.S. and Pakes, A. (1996), "The Dynamics of Productivity in the Telecommunications Equipment Industry," *Econometrica*, 64(6), 1263-1298.

O'Mahony, M., Castaldi, C., Los, B., Bartelsman, E., Maimaiti, Y. and Peng, F. (2008), "EUKLEMS - Linked Data: Sources and Methods," *www.euklems.net*.

O'Mahony, M. and Timmer, M. (2009), "Output, Input and Productivity Measures at the Industry Level: the EU KLEMS Database," *The Economic Journal*, 119(538), F374-F403.

Pakes, A. and Schankerman, M. (1984), "An Explanation into the Determinants of Research Intensity," in *R&D, Patents and Productivity*, ed. by Zvi Griliches, 209-232. Chicago: University of Chicago Press.

Popp, D. (2002), "Induced Innovation and Energy Prices," *American Economic Review*, 92(1), 160-180.

Schmookler, J. (1962), "Economic Sources of Inventive Activity," *Journal of Economic History*, 22(1), 1-20.

Senftleben, C. and Wielandt, H. (2012), "The Polarization of Employment in German Local Labor Markets," Number 13 in Sonderforschungsbereich 649: Ökonomisches Risiko, Wirtschaftswissenschaftliche Fakultät.

Song, Z., Storesletten, K. and Zilibotti, F. (2011), "Growing Like China," *American Economic Review*, 101(1), 202-241

Soskice, D. (1994), "Reconciling Markets and Institutions: The German Apprenticeship System," in *Training and the Private Sector*, 25-60. University of Chicago Press.

Spitz-Oener, A. (2006), "Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure," *Journal of Labor Economics*, 24(2), 235-270.

Staiger, D. and Stock, J.H. (1997), "Instrumental Variables Regression with Weak Instruments," *Econometrica*, 65(3), 557-586.

Stokey, N.L. (1998), "Are there Limits to Growth?," *International Economic Review*, 39(1), 1-31.

The New Palgrave Dictionary of Economics, Second Edition (2008), ed. Steven N. Durlauf and Lawrence E. Blume, Palgrave Macmillan.

Van Ark, B., Inklaar, R. and McGuckin, R.H. (2003), "The Contribution of ICT-Producing and ICT-Using Industries to Productivity Growth: A Comparison of Canada, Europe and the United States," *International Productivity Monitor*, 6, 56-63.

Van Reenen, J. and Yueh, L. (2012), "Why Has China Grown So Fast? The Role of International Technology Transfer," CEP Discussion Paper 1121.

Winkelmann, R. (1997), "How Young Workers Get Their Training: A Survey of Germany versus the United States," *Journal of Population Economics*, 10(2), 159-170.

World Bank (accessed 31.5.2012): "Gross National Income Per Capita 2009, Atlas Method and PPP."
http://www.damtp.cam.ac.uk/user/na/FoCM11/GNIPC.pdf.

Worldbank database (accessed on 14.06.2013): "CO2 Emissions (kt)",
http://data.worldbank.org/indicator/EN.ATM.CO2E.KT.

Worldbank database (accessed on 14.06.2013): "CO2 Emissions (Metric Tons Per Capita)",
http://data.worldbank.org/indicator/EN.ATM.CO2E.PC.

Worldbank database (accessed on 14.06.2013): "CO2 Intensity (kg Per kg of Oil Equivalent Energy Use)",
http://data.worldbank.org/indicator/EN.ATM.CO2E.EG.ZS.

Worldbank database (accessed on 14.06.2013/10.01.2014): "Research and Development Expenditure (% of GDP)",
http://data.worldbank.org/indicator/GB.XPD.RSDV.GD.ZS.

Worldbank database (accessed on 14.06.2013): "GDP (constant 2000 US$)",
http://data.worldbank.org/indicator/NY.GDP.MKTP.KD.

Worldbank database (accessed on 14.06.2013): "GDP Per Capita (constant 2000 US$)",
http://data.worldbank.org/indicator/NY.GDP.PCAP.KD.

World Interlectual Property Organization (WIPO) (accessed 14.06.2013): "Patent Grants by Patent Office (1883-2010) by Resident and Non-Resident",
http://www.wipo.int/ipstats/en/statistics/patents/

World Interlectual Property Organization (WIPO) (accessed 28.02.2012): "Resident Patent Filings Per US $ Million Research & Development (R&D) Expenditure (2001-2010)",
http://www.wipo.int/ipstats/en/statistics/patents/

World Interlectual Property Organization (WIPO) (accessed 14.06.2013): "Utility Model Grants by Office (1977-2010) Breakdown by Resident and Non-Resident",
http://www.wipo.int/ipstats/en/statistics/models/

Part V

Curriculum Vitae

Curriculum Vitae

Personal Information

Name:	Franziska Josefine Weiss
Date of Birth:	December, 20 1985
Place of Birth:	Frankfurt/M.
Nationality:	German

Education

09/2009 - 04/2014	PhD studies in Economics University of Zurich, Switzerland Supervisor: Prof. Dr. F. Zilibotti
09/2008 - 08/2009	Master of Science in Economics London School of Economics and Political Science, UK
09/2005 - 08/2008	Studies in Economics Eberhard-Karls-University, Tubingen, Germany
09/1996 - 08/2005	Kaiserin-Friedrich Gymnasium Bad Homburg, Germany

Professional Experience

09/2009 - 01/2014	Teaching Assistant and Research Associate Chair of Macroeconomics and Political Economy University of Zurich, Switzerland
09/2006 - 08/2008	Teaching Assistant Chair of Econometrics, Statistics and Empirical Economics Eberhard-Karls-University, Tubingen, Germany